

# The impact evaluation of public health insurance in Indonesia on access to care, financial protection, and health status

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# Abstract

## Objectives

This study evaluates the impact of an expanded national health insurance programme in Indonesia, focusing on three outcomes: access to health care, as measured by utilisation of health care services; financial protection, as measured by out-of-pocket (OOP) health expenditure and catastrophic health expenditure (CHE) indicators; and health status, as measured by levels of blood pressure and rates of diagnosed, treated and controlled hypertension.

## Research Methods

This study uses longitudinal data from the Indonesian Family Life Survey (IFLS) collected from 13 Indonesia's provinces, a total of 22,711 adults in 2007 who were followed up in 2014. The JKN enrollees are categorised into two groups: a *contributory* group who paid the premium voluntarily, and a *subsidised* group, paid by government. Each group is compared with the *uninsured* group who had no insurance coverage in both 2007 and 2014. Propensity score matching combined with difference-in-difference approaches are used to estimate the causal effect of the JKN programme. Heterogeneity of the effects of JKN is explored based on socioeconomic status, locality of residence (urban/rural), and availability of health facilities in the area.

## Results

The JKN programme increased the probability of individuals in the contributory group seeking outpatient and inpatient care as well as the volume of care provided. The subsidised group also showed increased utilisation, but the magnitude of the effect is much smaller than in the contributory group. In relation to financial protection, the JKN programme had no statistically significant effect on OOP health expenditure or catastrophic health expenditure. In terms of health outcomes, while the programme had no significant effect on systolic or diastolic blood pressure, the data suggest a positive effect on increasing awareness and treatment of hypertension among the contributory group and, to a lesser extent, the subsidised group.

## Conclusions

The JKN programme encouraged individuals in the contributory group to use more medical treatment, which had no effect, on average, on their health expenditure. The subsidised group appears not to have been able to maximise the JKN benefit, possibly due to other barriers in access to care, such as the inadequate supply of health facilities. The impact of the JKN programme on health status is yet to be confirmed as sufficient time has not passed for the programme's effect on health status to be realised

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## **Declaration**

I declare that this thesis is a presentation of my original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. Information included from other sources (e.g. journal articles and books) has been fully acknowledged and correctly referenced.

Darius Erlangga

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## Chapter 1 Introduction

In recent decades, achieving universal health coverage (UHC) has been a major health policy focus globally (UN Economic and Social Council, 2016; Marten et al., 2014; Savedoff et al., 2012). The inclusion of UHC in the health section of the United Nations Sustainable Development Goals (SDGs)<sup>1</sup> has created renewed momentum for national health insurance schemes (United Nations, 2016). Low- and middle-income countries (LMICs) face a particular challenge in achieving UHC due to poor public resources for health care, large population sizes and challenging geographic terrains (World Health Organization, 2010b). In addition, evidence suggests that access to health care and the burden of financial cost in LMICs tend to be worse for the poor, often resulting in forgone care (Kankeu et al., 2013; ILO, 2008; Stevens, 2004). Considering that the majority of the global poor live in developing countries, the progress in achieving UHC can, therefore, be regarded as one of the most important metrics in alleviating extreme poverty and improving collective welfare (Cotlear et al., 2015).

Three key problems have been identified by LMICs in their quest to moving closer to UHC: limited resources, over-reliance on direct payments, and the inefficient and inequitable use of resources (World Health Organization, 2010b). Consequently, there is a greater need for policy makers in LMIC countries to develop a more innovative health financing strategy, taking into account the strengths and constraints of each country. In the past two decades, many innovative health financing strategies have been implemented across the world (Palmer et al., 2004). This thesis, however, focuses on the role of health insurance. Health insurance refers to the pooling of pre-paid funds which allows for the transfer of risk by shifting the financial consequences of utilising health services from one individual to the collective pool (Folland, Goodman and Stano, 2014). Health insurance can be financed and managed in various ways. Ultimately, the decision about the type of health financing strategy a country needs to implement depends largely on the available financing resources and the size of the formal sector economy from which taxes and payroll contributions can be collected (Wang et al., 2012). Introducing and

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<sup>1</sup> SDG 3.8 is to “achieve universal health coverage, including financial risk protection, access to quality essential health-care services and access to safe, effective, quality and affordable essential medicines and vaccines for all” (Source: <https://sustainabledevelopment.un.org/sdg3>).

increasing the coverage of publicly organised and financed health insurance is widely seen as the most promising way of achieving UHC (Jowett and Kutzin, 2015; Maeda et al., 2014), since private insurance is mostly unaffordable for the poor (Kutzin, 2012).

Indonesia has attempted to establish national health insurance since the beginning of the 20<sup>th</sup> century. In January 2014, the government launched a new public health insurance programme called Jaminan Kesehatan Nasional (JKN) with the aim of covering 100 percent of the population. Prior to this reform, only selected groups within the population had access to health insurance, many of whom either worked in formal sector employment or were eligible to receive government assistance for health care (Thabrany and Mundiharno, 2012). The formal sector enjoyed better health insurance coverage, beginning as one of the benefits of taking up an employment. Meanwhile, the poor received several types of social assistance under the government's attempt to alleviate poverty, including the provision of health insurance.

The desire to bring all public health insurance schemes together never became a national priority. The economic crisis in 1997–1998, when the value of Indonesia's currency (IDR) dropped dramatically within six months from IDR 2,000 for 1US\$ to IDR 20,000 for 1 US\$, triggered a reformation era that brought significant restructuring to numerous supporting systems in Indonesia, including its health care system (Waters, Saadah and Pradhan, 2003; Sadli, 1998). One of the most historic steps in Indonesian health care reform was the ratification of the National Social Security Act in 2004, guaranteeing the provision of medical care and access to pensions and life insurance (Thabrany, 2012). Indonesia's constitution mandates that everyone shall have the right to obtain medical care. Thus, the ultimate aim of this new reform is to extend health insurance coverage to everyone, including non-poor people who work in the informal sector, who had been overlooked prior to the introduction of JKN programme. This thesis is aiming to evaluate whether the JKN programme has been successful in meeting its objectives.



Evaluating the effectiveness of health insurance, however, is not straightforward because those who are insured may have different characteristics that also influence health care consumption. This is often called insurance selection bias. The proper evaluation of health insurance needs to control this insurance selection bias in order to establish the causal effect of health insurance (Ali, Cookson and Dusheiko, 2017). In statistics, the gold standard for impact evaluation is the randomised study. Randomisation, if done correctly, is able to eliminate any confounding factor, including insurance selection bias. Randomised studies are very common in medicine, but their application in health policy evaluation is still limited in developing countries. If the health programme of interest has been implemented nationally, a randomised study to evaluate the impact of that programme is no longer feasible. Therefore, non-randomised studies can still have their place in informing policymakers of the health policy's impact. The use of longitudinal data in non-randomised studies can also improve the robustness of the findings, although it is more data-intensive than using cross-sectional data (Jones and Rice, 2011).

For the reason mentioned above, this thesis will focus on the impact of the JKN programme on newly-insured individuals, who were previously uninsured in the baseline period and enrolled in the JKN programme in the follow-up year. For the analysis, the Indonesia Family Life Survey (IFLS) – the only longitudinal data available in Indonesia that covers the periods before and after the introduction of the JKN programme – will be employed. The rich information provided by the IFLS data enables the identification of the insurance status of individuals over time. IFLS data also provide a great amount of information on health care utilisation, health expenditure, and health status at an individual level (Strauss, Witoelar and Sikoki, 2016). Furthermore, the IFLS survey collected information of the availability of health care facilities and characteristics of the community which may provide additional supply-side control for health insurance analysis.

Demand for health insurance is generated by the need to access medical care that is not affordable in the absence of health insurance (Folland, Goodman and Stano, 2014). When an individual already has access to health care services, the next step is to decrease the loss of income due to increased use of medical treatment. By meeting the demand for health care without incurring excessive expenditure, it is expected

that there will be an improvement in an individual's health (Comfort, Peterson and Hatt, 2013). Therefore, the purpose of this thesis is to evaluate the effectiveness of the JKN programme by focusing on three broader objectives:

1. Access to health care measured by utilisation of health care services
2. Financial protection measured by out-of-pocket (OOP) health expenditure and catastrophic health expenditure
3. Health status looking at blood pressure and hypertension rate

I identify several key gaps in the literature in the context of Indonesia:

- A lack of health insurance studies that analyse inpatient care services in Indonesia, even though this outcome is likely to be more sensitive to the presence of health insurance.
- OOP health expenditure analyses in Indonesia have not looked at self-treatment expenditure.
- No study has looked at the impact of health insurance on health status in Indonesia.
- This is the first study to evaluate the effectiveness of the JKN programme using IFLS data.

This thesis is organised into 10 chapters:

- 1) Chapter 2 provides an overview of basic health insurance theories, then proceeds to discuss it into health financing system in LMICs with specific reference to the context in Indonesia.
- 2) Chapter 3 presents the background information of Indonesia followed by the history of the health insurance programme before and after the 1998 economic crisis, and the detail of the JKN programme.
- 3) Chapters 4 and 5 present a systematic review of the effect of health insurance in LMICs in terms of access to care, financial protection and health status. In chapter 4, I provide an overview of the systematic review and identify the review which has the best quality among the selected reviews. The search strategy of the chosen best review is updated to include more recent evidence and its findings are presented in chapter 5.

- 4) Next, chapter 6 will present an overview of regression method to deal with non-normally distributed variables. Then, it will describe the difficulties of selection bias in health insurance evaluation study and explain statistical methods that may overcome this bias, informed by the review of the literature in chapter 5.
- 5) Chapters 7 to 9 present the empirical results of the JKN programme evaluation analysis. Chapter 7 examines the JKN effect on utilisation of health care at the individual level. Chapter 8 analyses the effect on OOP health expenditure at both individual and household levels and the incidence of catastrophic health expenditure at household level. Chapter 9 explores the impact of JKN on blood pressure and hypertension in terms of prevalence, awareness, treatment and controlled rate.
- 6) Finally, Chapter 10 concludes with a discussion of the JKN effect on health care utilisation, financial protection and health status in Indonesia based on the current health care systems and the empirical studies provided in the previous chapters, with a view to drawing policy implications for the future improvement of health care financing. In addition, study limitations are discussed and suggestions for further studies are provided.



## **Chapter 2 Theories in health insurance**

This chapter will provide an overview of health insurance theories including the demand for health insurance, moral hazard, adverse selection, and the need for governments to intervene in the provision of health insurance. Furthermore, it will give an overview of the most common health insurance systems in the low- to middle-income countries (LMICs), with a special focus on social health insurance because it has been adopted by Indonesia to extend health insurance coverage to the poor and workers in the informal sector.

### **Section 2.1 Health insurance characteristics**

#### **2.1.1 Demand for health insurance**

When faced with random events of illness, individuals often encounter situations in which they are required to spend unpredictable sums of money to restore their health, to as close to their condition before the illness. In order to protect their income from unpredictable shocks relating to illness, individuals can either borrow money from a financial institution or their family, or set aside a proportion of their income into savings (Brown and Churchill, 1999). Borrowing money might not be a viable option for the poor since credit institutions tend to have less confidence in the poor's ability to settle loans. Savings might be sustainable for dealing with minor illness, but not suitable for more catastrophic medical bills (for example, heart surgery or stroke management), even for more affluent individuals. Individuals might also need to curtail a big proportion of their consumption to pay off sizeable medical bills when they have no insurance (Cutler and Zeckhauser, 2000). With its ability to pool the risk from other individuals, insurance is superior to protect one's consumption pattern from unpredictable illness consequences. Thus, a demand for health insurance can be seen as a demand for certainty to cover the costs of seeking medical treatment (Friedman and Savage, 1948).

In the event of random illness, insurance is able to pool the risk of financial impact due to illness and make the risk more predictable by requiring individuals to pay a small fixed premium upfront (Blomqvist, 2011, p.258). This is one of the most attractive features of insurance; insurance is able to reduce the financial risk for one

person and spread the risk to everyone else in the pool. In other words, insurance is able to transfer income from the healthy pool to the sick pool while still maximising total utility (Nyman, 2003; Cutler and Zeckhauser, 2000).

Assuming the premium is set at an actuarially fair price, the expected utility theory predicts that when the expected utility of insurance exceeds the expected utility of no insurance, an individual will purchase such insurance (Mas-Colell, Whinston and Green, 1995, pp. 187–188). However, the decision to purchase health insurance also depends on people's willingness to pay for the insurance, which is influenced by the value of marginal medical care to one's utility and the financial risk avoided (Manning and Marquis, 1996). In a study assessing the relationship between premium reduction and participation in employer-sponsored health plans by low-income workers, a lower premium increased participation in health insurance plans, but even full subsidies did not induce all workers to purchase health insurance (Chernew, Frick and McLaughlin, 1997). It is suggested that how people value their healthy times in their life can also interfere with the value of health insurance (Cutler and Zeckhauser, 2000). If individuals place little value on money when sick, health insurance becomes unnecessary. In an extreme case, some individuals may still hold a traditional belief that favours non-materialistic well-being which reduces the need for money. In a less extreme case, individuals may not have choices about the pleasurable activities they can engage in, thus making them indifferent to whether they are sick or not.

### **2.1.2 Moral hazard**

Moral hazard describes any change in consumer behaviour occurring in response to the decision to insure (Pauly, 1968). Through the pooling of risk, health insurance decreases the marginal costs of medical care to consumers and consumers anticipate this price reduction by utilising more health care services (Folland, Goodman and Stano, 2014). Consumers, therefore, tend to overuse care, more than they would have if they were paying for the medical care at full cost by themselves. However, the cost of medical care stays the same for the health provider. Thus, the additional health care consumed is less than the actual cost which reflects a welfare loss (Cutler and Zeckhauser, 2000).

In classic insurance theory, the cost sharing mechanism is an economic incentive to discourage moral hazard (Folland, Goodman and Stano, 2014). This incentive may include coinsurance, co-payment and deductibles. Coinsurance refers to the percentage of medical bills paid by the insured; co-payment refers to the fixed payment paid by the insured per one use of care; and deductible refers to the minimum amount the consumer has to pay out-of-pocket before the insurer covers the bills. The requirement of cost sharing discourages unnecessary claims or visits by alerting the insured to the true costs of purchased medical treatment.

Empirical evidence regarding moral hazard comes from the Rand Health Insurance Experiment that randomised the participants into different insurance plans ranging from zero cost sharing to 80 percent cost sharing. Participants with cost sharing made one to two fewer physician visits annually and had 20 percent fewer hospitalisations than those with no cost sharing (Manning et al., 1987). The magnitude of moral hazard is therefore positively related to the generosity of the insurance (Manning and Marquis, 1996; Zeckhauser, 1970). Thus, it creates a tension between offering a more generous plan which provides better financial protection and placing stricter cost sharing mechanisms to reduce moral hazard. The use of cost-sharing also receives some criticism as it may prevent the consumption of necessary care (Fels, 2017), in particular among low-income households (Kim, Ko and Yang, 2005; Lohr et al., 1986, pp.20–28; Beck, 1974) and chronically-ill populations (Hsu et al., 2006).

The conventional concept of moral hazard applies to certain routine medical treatments for minor illness or elective surgeries (Pauly, 1983). For example, an insured individual may visit the outpatient clinic more often to seek treatments for conditions such as colds and headaches which can otherwise be treated with over-the-counter medicine from a pharmacy. An insured pregnant woman with no complications might also elect for a caesarean birth but choose differently if she did not have the insurance. However, this theory is not appropriate in explaining the demand for treatment of major illness because it implies that a healthy insured

individual would also demand more open heart surgery, for example, just because the insurance reduces its price to zero (Nyman, 2003).

An alternative to the conventional understanding of moral hazard described above is the concept of essential moral hazard. Nyman (1999) proposed that health insurance is also a demand for an income transfer from the healthy to the ill. The insured individuals would gain additional benefits from the transferred income when they became ill. This income transfer therefore allows the insured to gain access to health care that would be otherwise unaffordable (Nyman, 2003). Considering the above example of open-heart surgery, its prices may fall for all who purchase health insurance, but only those who have a heart condition will respond to this price reduction. Since only the ill consume more medical care due to this income transfer, the additional care generates a welfare gain. Furthermore, Nyman's theory assumes that the loss of income by the healthy would not generate substantial reductions in health care consumption, assuming the income elasticity of the healthy is close to zero.

There have been very few empirical studies that test the argument for efficient moral hazard. A simulation study using the Medical Expenditure Panel Survey of the American population showed empirical evidence of efficient moral hazard but it varies from one disease to another, with diabetes and cancer having the largest proportion of efficient moral hazard (Nyman et al., 2018). Another study argued that inefficiency caused by moral hazard is influenced by the severity of the illness and this correlation is likely to be parabolic: less problematic for minor and major conditions but most problematic for intermediate cases (Eisenhauer, 2006).

While the above discussion has only focused on the moral hazard generated by the consumer, there is also the threat of provider-generated moral hazard, especially in a health system that still uses the fee-for-service method as its provider payment system. It is also often called supplier induced demand (SID). While a doctor acts as the agent of the patient by helping in the interpretation of the patient's signs and symptoms, and delivering the medical treatment to cure the patient's condition, the doctor is also a supplier whose income is related to the volume of services delivered



(Fuchs, 1978). In a fee-for-service setting, it creates strong economic incentives for the doctors to overprescribe their services and influence patients' decisions towards services which yield the highest revenue (Evans, 1974).

Empirical data on SID has attracted debate among the experts (Rice and Labelle, 1989; Feldman and Sloan, 1988). Early evidence showed that the increased availability of surgeons significantly affected surgery rates (Cromwell and Mitchell, 1986; Evans, 1974), but those studies have been criticised for having flawed econometric specifications so that the evidence of supplied-induced demand is confounded by other coefficients (Feldman and Sloan, 1988; Auster and Oaxaca, 1981). More recent evidence showed that, on average, a 1 percent increase in the supply of doctors will result in a 0.46 percent increase in the quantity of services demanded (Peacock and Richardson, 2007). However, this induced demand may not always harm the patients: a study in Norway found that increased availability of physicians is associated with greater consumer satisfaction, assuming it is a good proxy to measure patient's utility (Carlsen and Grytten, 2000).

In the context of Indonesia, moral hazard due to the JKN programme may pose a problem in overcrowding the public health facilities, both primary care clinic and hospitals. However, it can also be argued that the moral hazard effect of the JKN programme may be efficient instead as it may help its enrolees access the care that would have been unaffordable without the insurance. In addition, supplier-induced demand may not be problematic in the context of Indonesia because the JKN programme does not use fee-for-service payment system to reimburse the costs of medical treatment consumed by its enrolees.

### **2.1.3 Adverse selection**

Adverse selection is the consequence of asymmetric information between the consumers, who know more about their expected health expenditure in the future, and the insurer, which is assumed to have no means of predicting the health status of the consumers (Rothschild and Stiglitz, 1976; Akerlof, 1970). Sicker consumers will be attracted to the insurance plan which provides more generous benefits, while the healthier consumers prefer to enrol in a plan with lower premiums compensating for

less generous benefits. Thus, the higher health risks tend to drive out the lower health risks from the market. Adverse selection therefore creates three types of inefficiencies (Cutler and Zeckhauser, 1998):

- Firstly, the premium will not be set at the marginal costs for the consumers. Adverse selection forces the more generous plans to increase their premium to compensate for higher risk pooling.
- Secondly, risk spreading is no longer effective. The higher premium due to adverse selection further deters healthier people from joining the more generous plan. Assuming no intervention from the government, the insurance market would be divided into two ends in which low-risk and high-risk individuals are separated from each other (Blomqvist, 2011). The high-risk would have to pay higher premiums to the point that it is no longer affordable, leaving them unprotected.
- Thirdly, the insurer may manipulate or alter their benefits in order to deter the sick and attract the healthier. The insurer has an incentive to distort their benefits in order to gain more profits by enrolling greater numbers of healthier people. The under provision of services to high-risk patients is often termed 'skimping' while 'cream-skimming' refers to the over provision of services to low-risk patients (Ellis, 1998). Consequently, the surviving insurance plans would only offer limited benefits which means that the high-risk individuals have no protection against more catastrophic medical bills (Blomqvist, 2011).

Cutler and Zeckhauser (1998) provided an example of classic adverse selection from a case study on employer-sponsored insurance plans for employees in an American private university. The first plan adopted a Preferred Provider Organisation (PPO) system which offered more freedom to see any GPs and specialists without referral, whereas the second plan adopted a Health Maintenance Organisation (HMO) system which provided managed care to their enrollees. Following a series of university policies to contain the rapidly-rising health care expenditure, the HMO plan was able to reduce their premium while the PPO plan kept their premium constant. As a result, the enrolment rate for the PPO plan dropped from 20 percent to 9 percent within two years and those who switched to the HMO plan were healthier and younger than those who remained. The PPO plan consequently collapsed due to unsustainable risk

pooling and rising health care costs. Adverse selection creates a death spiral which will force a riskier plan out of business (Cutler and Zeckhauser, 1998).

Voluntary health insurance models, including community-based health insurance which has become popular among LMICs in recent decades, are more susceptible to adverse selection and therefore suffer from low enrolment rates (Carrin, 2003, pp.6–11). Wang et al. (2006) documented adverse selection in the voluntary health insurance scheme for the rural population in China. The scheme used the household as the unit for enrolment to reduce adverse selection, but the scheme only allowed partial enrolment. The authors found that the non-enrolled individuals in the partially-enrolled households were healthier compared to the enrolled individuals in the partially-enrolled households (Wang et al., 2006). Furthermore, the government subsidy to encourage enrolment among the poor did not help to reduce inequity in enrolment (Zhang and Wang, 2008).

The case for adverse selection in Indonesia may be more problematic than moral hazard. Since the JKN programme accepts voluntary membership without restriction on pre-existing condition, sicker individuals are more likely to enrol and consume more medical care. Compulsory enrolment may alleviate this adverse selection problem, but it may be proven difficult to enforce it in Indonesia considering the decentralisation system adopted since early 2000s. More discussion about the background of Indonesia political and health system will be explained in Chapter 3.

#### **2.1.4 Government intervention in demand for health insurance**

The health care market is beset with asymmetric information among consumers, health providers and insurers, and it thus creates an adverse selection problem. This asymmetric information also prompts supplier induced demand in which the health providers have an incentive to prescribe more health care services to primarily increase their income. In addition, certain health issues often have externalities, such as vaccinations, smoking and obesity (Cutler, 2002, pp. 2146–2147). Therefore, private market in health care may create inefficiencies and welfare-decreasing for the society. A government may be capable of allocating resources more efficiently or of

distributing income more equitably compared to the private health care market (Stiglitz, 1989).

Two general economic theories explain the motivation for governmental intervention in health care systems. The first is the public interest theory in which a government attempts to fix market failure in order to increase efficiency and equity (Santerre and Neun, 2010, p. 248). However, government intervention is predicted to create more inefficiencies and inequity. The second theory is the special interest group theory in which the politicians in power have an incentive to implement policies that support special interest groups, shifting the wealth away from the general public (Becker, 1983). Even though a group of consumers can have a large number of members, individuals in a special interest group are collectively more powerful, more organised and share a common single interest. In the real world, it is likely that governments are motivated for both reasons (Santerre and Neun, 2010).

In the context of Indonesia, both reasons are equally likely in influencing the establishment of a unified public health insurance system. Acknowledging the importance of safety net for the most vulnerable after the monetary crisis in 1998 and the failure of existing government-run health insurance system in covering the informal workers who are more likely to be uninsured, the government passed the **SJSN Law No. 40/2004** as the first law regulating the establishment of the Social Security System in Indonesia that includes health insurance and pension. However, various stakeholders in employer associations challenged the implementation of this law. They opposed the mandatory nature of the system arguing that it would hurt their businesses by placing more burdens on them in addition to the current contribution for social security (Thabrany, 2012). Instead, they proposed that the market system should provide the health insurance. The implementation of the SJSN law was further delayed by a long debate among existing public health insurance providers on who would administer the national social security programme. This political debate among various vested interest parties was responsible for the late establishment of the solid social security programme in Indonesia (Aspinall, 2014)

A government may act as a provider of health insurance or impose regulations on the existing health insurance market. The WHO has advocated for a greater government role in ensuring that everyone has access to health care services and does not experience a catastrophic financial event associated with access to care (World Health Organization, 2010a). This is often described as universal health coverage (UHC). There are four guiding principles in the development of a health financing system capable of delivering UHC: revenue raising, pooling revenues, purchasing services, and benefit design and rationing mechanisms. In the context of this thesis, I will focus in more detail on the role of the government in raising and pooling revenues.

## Section 2.2 Health financing system in the low- and middle-income countries

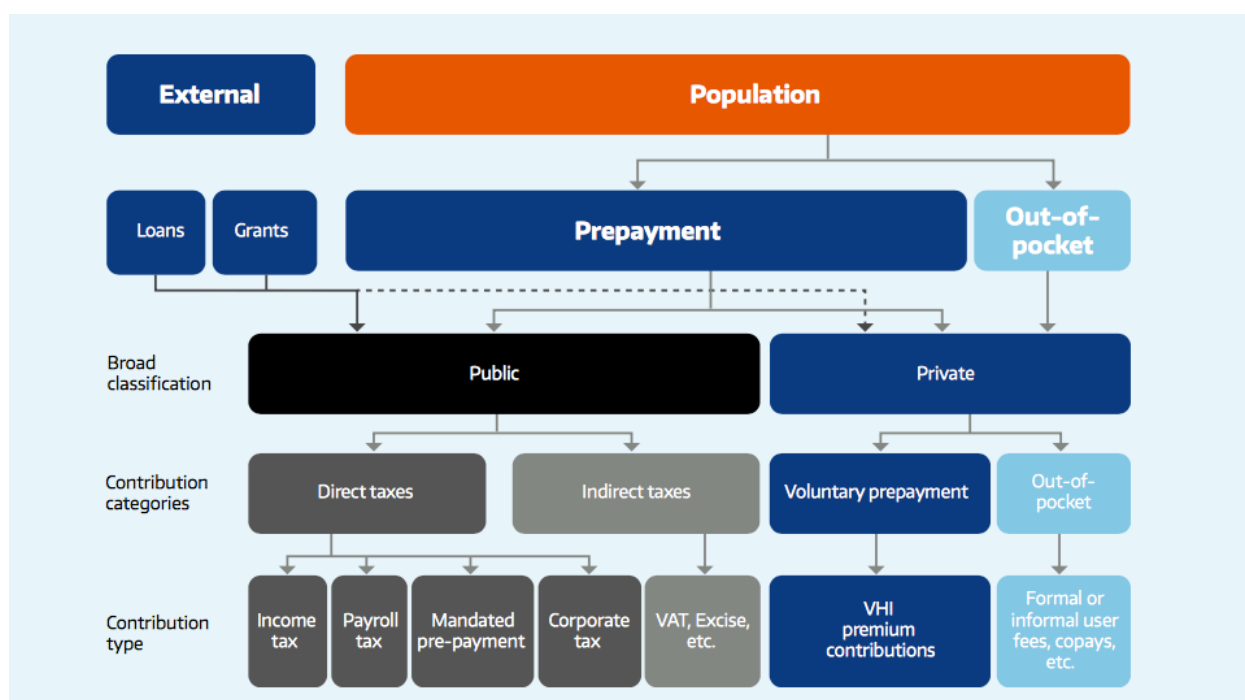


Figure 2-1 Revenue sources and contribution mechanisms. Source: WHO (2017)

Figure 2-1 presents an overview of the major revenue sources and contribution mechanisms. Populations contribute to health financing systems either by paying out-of-pocket at the point of use or making a pre-payment in advance and in exchange for full or partial coverage against future health expenditure. In general, health insurance schemes can be managed by either the public or private sector.

Premium contributions for private insurance are typically voluntary, whereas public insurance generates revenues from either mandatory pre-payment or taxes, which can be direct taxes or indirect taxes. In addition, private insurance may impose cost-sharing mechanisms to discourage excessive use of health care services (i.e. moral hazard) and this type of payment contributes to out-of-pocket payment. Public insurance can also charge some cost sharing but only at the margins and it is aimed to generate more revenue rather than to discourage use of care (Chalkley and Robinson, 1997, pp. 28–29). Informal or unofficial payment also contributes to out-of-pocket payment, particularly in developing countries and countries undergoing economic transitions (Ensor, 2004; Lewis, 2007).

Gottret and Schieber (2006) described four types of health insurance that are commonly used in LMIC to raise revenues and pool risks:

1. State-funded systems or general tax-funded systems
2. Community-based health insurance
3. Private health insurance
4. Social health insurance

In this section, I will briefly explain the characteristics, advantages and disadvantages of each type and provide more detail on social health insurance as this is the type of insurance that is being implemented in Indonesia.

Table 2-1 Characteristics of health insurance systems

<b>Type of insurance</b>	<b>Revenues sources</b>	<b>Nature of contributions</b>	<b>Earmarked for health?</b>	<b>Membership</b>
<b>State-funded insurance</b>	Direct/Indirect taxes	Mandatory (taxpayers)	No	All citizens
<b>Community-based health insurance</b>	Prepayment premium	Voluntary	Yes	Contributing members (and their dependents)
<b>Private insurance</b>	Prepayment premium	Voluntary	Yes	Contributing members (and their dependents)
<b>Social health insurance</b>	Contributions from wages and salaries	Mandatory	Yes	Contributing members (and their dependents)

Source: Adapted from (Hsiao et al., 2007, p.16)

### 2.2.1 State-funded insurance

State-funded insurance is the most widespread health insurance system in the world, used by more than half of the countries of the world (Savedoff, 2004). This system is often called a national health service system because it provides access to a network of public health providers funded through general tax revenues for the entire population. Theoretically, this system avoids the problem of adverse selection and risk selection by providing health care services to everyone. However, moral hazard on routine medical services still poses a substantial threat that may contribute to rising health expenditure. Furthermore, this system requires a strong tax administration in place in order to raise sufficient revenues (Wagstaff, 2009).

In general, state-funded insurance has three strengths:

- **Comprehensive coverage of the population.** This system can be easily extended to cover 100 percent of the population because it does not depend

on specific contributions. Due to its comprehensive coverage, its risk management can be potentially more effective and equitable than other financing systems (Gottret and Schieber, 2006).

- **Large scope for raising revenues.** The government can generate revenues from direct taxes (for example, personal income tax, corporate income tax and property tax), indirect taxes (for example, value-added taxes and import taxes) or a mixture of both (Wagstaff et al., 1999). An earmarked tax can also be utilised to make the system more transparent and responsive to taxpayer preferences (Wilkinson, 1994). Due to the larger scope for raising revenues, the burden of contribution can be extended to a larger share of the population, implying a potentially more effective risk spreading mechanism. However, not all types of taxes are equitable and effective in raising revenues. A more recent body of literature argues that progressive taxes are more preferable to regressive taxes as the latter is associated with higher post-neonatal mortality, infant mortality and under-5 mortality LMICs (Reeves et al., 2015).
- **Less complicated governance with the potential for cost control.** This system allows for integration between the provider and the payer roles, providing an opportunity to organise the health system more efficiently by lowering the costs of administration. In contrast, a more fragmented system tends to have disordered relationships, poor information flows and misaligned incentives that lead to degraded care quality and increased costs (Cebul et al., 2008).

State-funded insurance also has some weaknesses which are described below.

- **Unstable funding.** The funding for health is subject to annual budget negotiations and has to compete with other government priorities, such as education, infrastructure and defence. Furthermore, the state-funded system is more vulnerable to changes in political priorities (Gottret and Schieber, 2006).
- **Potential inefficiencies in health care delivery.** National health insurance has been the subject of criticism for its inefficiency in delivering care to the population concerning ageing infrastructure, long waiting lists for non-emergency care and unresponsive staff. If the health care provider is employed as a civil servant, it tends to have fewer incentives to innovate and



be less responsive to consumers' needs, compared with employment in a more competitive mechanism (Savedoff, 2004). Consequently, this system is more likely to receive lower levels of public satisfaction compared to social health insurance (van der Zee and Kroneman, 2007; Elola, 1996).

### **2.2.2 Community-based health insurance**

Community-based health insurance (CBHI) is found throughout the world, but it is particularly prevalent in Sub-Saharan Africa. It is sometimes referred to as mutual health organisations, micro insurance schemes or *mutuelles de santé* (Gottret and Schieber, 2006). Despite the wide heterogeneity of CBHI schemes around the world in terms of population coverage, regulation, management and benefits, CBHI can be identified by three main aspects: affiliation is based on community membership with the strong involvement of the community in management; enrolees are excluded from other kinds of health insurance; and enrolees share a set of social values, for example, voluntary participation, solidarity and reciprocity) (Jakab and Krishnan, 2001). The strength of CBHI lies in its ability to fill in the gaps left by the existing health financing schemes (Dror and Jacquier, 1999). The target populations of CBHI schemes are often individuals who are excluded from existing health insurance, such as individuals working in informal sectors. Employees in formal sectors may already receive health insurance from their employers or a social health insurance system. Thus, CBHI is theoretically able to extend coverage to those excluded groups who would otherwise not be insured (Jakab and Krishnan, 2001). For example, Ghana launched a new reform in 2004 to increase health insurance coverage to informal workers by providing mutual health insurance schemes at a district level (Kusi et al., 2015). Similarly, Tanzania also launched two separate voluntary insurance schemes for informal workers based on where they live: the Community health fund (CHF) for rural dwellers and *Tiba kwa Kadi* for urban dwellers (Kapologwe et al., 2017).

Despite its potential, CBHI suffers from some weaknesses that prevent it from contributing more significantly to the overall health care system. First, CBHI tends to work in small and poor communities which limits its potential to pool the risk effectively. Because of its limited capability in risk pooling, CBHI can only offer limited benefits packages for its enrolees. Inadequate benefits packages have been

described as a barrier to enrolment and renewal decisions in some CBHI schemes (Dror et al., 2016). The small scale of CBHI also implies weak managerial capacity that is a critical factor in improving the performance of CBHI (Carrin, Waelkens and Criel, 2005).

Secondly, poor people who are the target population of CBHI are likely to have stricter budgets, limiting their ability to afford insurance premiums, which further limits the risk pooling ability of the CBHI (Kapologwe et al., 2017). As a consequence of unattractive benefits packages and low willingness to pay among the poor, CBHI tends to suffer from low enrolment rates which threatens its sustainability in the long term (Dror, 2002; De Allegri et al., 2009). Indonesia introduced a CBHI programme named “Dana Sehat” in 1969 but this also suffered from a low enrolment rate due to limited benefits package. Consequently, it was discontinued in the late 1990s (Thabrany, 2012).

### 2.2.3 Private health insurance

Private health insurance is defined as any health insurance provided by private organisations and paid for by voluntary mechanisms (Sekhri and Savedoff, 2005). It is distinguished from social health insurance by the lack of mandated payments which form an essential part of social health insurance (Gottret and Schieber, 2006). In some LMICs, private health insurance can be the only means of protecting against future catastrophic health expenditure and commonly it covers upper-middle and high income individuals, often working in the formal sector (Sekhri and Savedoff, 2005). In contrast, high-income countries tend to have private health insurance as secondary coverage, except in the USA, Switzerland and Australia. Private insurance can function as a **supplementary** insurance that provides a greater choice of providers (for example, the UK and Sweden), as a **complementary** insurance to pay cost sharing in a publicly funded health insurance system (for example, France and Belgium) or as a **substitutive** insurance for the excluded population, customarily for the high earners (for example, Germany) (Thomson and Mossialos, 2009, p.13).

### **Strengths of private health insurance:**

- Private health insurance affords financial protection (compared with out-of-pocket expenditure) and enhanced access to health services for those who can afford it. Thus, it can help to redirect tax revenues to provide health care for the poor (Sekhri and Savedoff, 2005).
- Private insurance can fill in the gaps created by an existing publicly funded health insurance system by acting as a supplementary, complementary or substitutive insurance. It can also enhance patients' access to timely hospital care in some OECD countries (for example, Ireland, Australia and the UK) (Siciliani and Hurst, 2005).
- Private insurance may be able to increase service capacity and promote innovation given enough room for market competition. Private insurers can be more receptive to individuals' demands and find innovative and flexible coverage plans (Tapay and Colombo, 2004, pp. 287–288).

### **Weaknesses of private health insurance:**

- Private plan is unable to solve other financial barriers to access, for example, affordability and price volatility) (Gottret and Schieber, 2006).
- Private health insurance may create two-tiered access to health care services (Tapay and Colombo, 2004, pp. 281–282). When the health providers are able to operate in both public and private health insurance, two-tiered access may induce an unequal form of access that is pro-rich. Health providers may focus their time and energy on serving patients with private insurance, thereby abandoning patients covered by public health insurance.
- Private insurance system tends to increase total health expenditure in several OECD countries because they bring more financial resources into the health care system, do not have the strict cost-control that is found in the public insurance system, and have less bargaining power over the price and quantity of care (Tapay and Colombo, 2004, p.293).
- There are high administrative costs, especially from overhead costs such as underwriting and marketing, which are mostly absent in public insurance (Woolhandler, Campbell and Himmelstein, 2003).

#### 2.2.4 Social health insurance (SHI)

While more than one definition of social health insurance exists, two characteristics emerge as the most important in almost all existing SHI schemes. It is funded through a mandatory contribution, typically through the payroll taxes of formal sector workers, and a quasi-independent organisation is responsible as the managing body and the payer (Wagstaff, 2010b; Normand and Busse, 2002). SHI can be crudely distinguished from state-funded insurance by its clearer link between contributions and the benefits entitlements promised to the enrolees (Hsiao et al., 2007, p.15). Since SHI was historically designed to cover employees in the formal sector, low- and middle-income countries often need to design a special arrangement for citizens not employed in formal sectors. Countries may vary in this special arrangement, for example, the Philippines and Vietnam allow both formal and informal workers to contribute to one unified scheme, whereas China and Mexico have a separate contributory scheme instead (Wagstaff, 2010b). The advantages and drawbacks of social health insurance are described below.

##### **Strengths of social health insurance:**

- **Risk-independent and transparent contributions.** Contributions are not linked to the health status of members and can normally be extended to their direct family (Saltman, 2004). Social contributions may be easier to collect as the citizens can trace the money earmarked for health spending (Gottret and Schieber, 2006, p. 86). The relationship between the insurer and the enrolees tends to be more contractual which demands a clearly defined set of benefits entitled to the enrolees (Normand and Busse, 2002, p.73).
- **Less dependence on budget negotiations.** Compared to state-funded insurance, SHI is less sensitive to budget negotiations and political pressure (Hsiao et al., 2007, p.15). A government may subsidise contributions for specific populations (for example, poor people and veterans) and this subsidy does not free from budget negotiations either.
- **Strong solidarity value.** SHI can be viewed as a way of empowering citizens through participation. In countries with long-established SHI systems (for example, Germany and the Netherlands), SHI is not regarded solely as insurance, but rather *“a key part of a broader structure of social security and*

*income support that sits at the heart of civil society” (Saltman, 2004, p.6).*

Strong support from the population may contribute to the sustainability of SHI systems in those countries (Gottret and Schieber, 2006, p.86) and high levels of satisfaction among the population (Normand and Busse, 2002, p.75).

- **High degrees of redistribution.** Both state-funded insurance and SHI are more progressive than privately-funded health insurance but SHI tends to be less progressive than state-funded insurance (Wagstaff et al., 1999).

#### **Weaknesses of social health insurance:**

- **Complex and expensive to manage.** SHI requires a more complex system involving many different agents and complicated tasks. The managing organisation, often called sickness funds, has to collect social contributions, negotiate contracts with providers, reimburse the care used by the insured, and manage the collected funds (Gottret and Schieber, 2006). Another important issue related to SHI is evasion and avoidance of SHI contributions, especially among the non-poor employees who work in the informal sector which forces sickness funds to spend extra money. This leads to higher administrative costs together with its already complex management (Wagstaff, 2009).
- **Escalating health expenditure.** Some empirical evidence has suggested that SHI leads to higher health expenditure. Looking at 28 countries in Eastern Europe and Central Asia, out of which 14 countries switched from a tax-funded system to SHI, Wagstaff and Moreno-Serra (2009) demonstrated that SHI raises health spending per capita by 11 percent. Wagstaff (2009) also conducted a similar analysis, but on OECD countries only, and he found that SHI raises per capita total health spending by 3 percent. The increase in health spending, however, does not contribute to better health outcomes (Wagstaff, 2009; Wagstaff and Moreno-Serra, 2009).
- **Negative economy impact of payroll contributions.** SHI may contribute to a growing informality of the economy that may reduce the government’s ability to collect tax revenues (Wagstaff, 2010b). Informal workers typically pay less contribution to an SHI system compared with formal workers. For instance, informal workers pay a flat-rate contribution in Vietnam and Indonesia and report just enough income to pay the lower rate contribution in Mexico and

Chile (Baeza and Packard, 2006, pp. 104–107). Some individuals therefore have an incentive to avoid working in the formal sector to retain more income and keep the health coverage.

In the 2010 World Health Report, the WHO did not recommend any particular type of health financing model to attain the universal health coverage goal. Therefore, many low- and middle-income countries have experimented with different mechanisms of raising revenues, strategic purchasing and provider payment systems, taking into account the strengths and limitations of each system. Indonesia has been experimenting with its health financing system over the past 20 years and finally introduced the national health insurance (Jaminan Kesehatan Nasional / JKN) programme that unifies all separated, non-private insurance schemes into a single payer system with myriad rules for collecting contribution. In the next chapter, more detail on the history of public health insurance system in Indonesia will be explained with particular focus on the JKN programme.

## Chapter 3 Profile of Indonesia

### Section 3.1 Demographic, economic, and health profile

Indonesia is a large archipelago country consisting of 17,508 islands but only 58 percent of them are inhabited. It is the largest country in the Southeast Asian region in relation to both country and population size. The five largest islands are Papua, Kalimantan, Sumatra, Sulawesi and Java (the most populous island). With its capital, Jakarta, located in Java, it is expected that Java will undergo more rapid facilities development compared to the other islands, including hospitals, clinics and public health centres.



Figure 3-1 Indonesia map

(source: CIA publication - <https://www.cia.gov/library/publications/the-world-factbook/>)

Indonesia is divided into three time zones: **Western** (Sumatra, Java, West and Central Kalimantan), **Central** (the rest of Kalimantan, Sulawesi, Bali and Nusa Tenggara) and **Eastern** (Maluku and Papua) Indonesian time. Anecdotally, this division also characterises the degree of economic development among the provinces in Indonesia. The eastern region tends to be less developed than the western and central regions. Papua consistently has more than 20 percent of its population living in extreme poverty (BPS Indonesia, 2017b).

Indonesia also faces significant challenges in relation to natural disasters. Indonesia lies on a major juncture of the Earth’s tectonic plates making it susceptible to seismic activity and tsunamis. A recent major tsunami hit Aceh province in 2004, killing approximately 131,000 people and leaving 500,000 people displaced from their homes (Cluff, 2007). In addition, Indonesia has a very large number of active volcanoes in the world with 127 active volcanoes. Fortunately, fatalities caused by volcano eruptions have been minimised due to active surveillance and quick responses from the government.

In 2015, Indonesia had population of 258 million people, or about 3.5 percent of the world’s population (BPS Indonesia, 2016), but its population is unevenly distributed. The population density outside Java and Bali is under 250 people/km<sup>2</sup>, in contrast with over 800 people/km<sup>2</sup> in Java and Bali. Thus, even though Java island represents only 7 percent of the total land area, it is home to more than 60 percent of the Indonesian population. Over time, Indonesia’s demography has changed due to a decline in the fertility and mortality rates. Figure 3-2 depicts the change in age distribution from 1970 to 2010 with a projection to 2050 (McDonald, 2014). Compared to 40 years ago, Indonesia’s working age population is now the largest group and the youngest age group is growing more slowly.

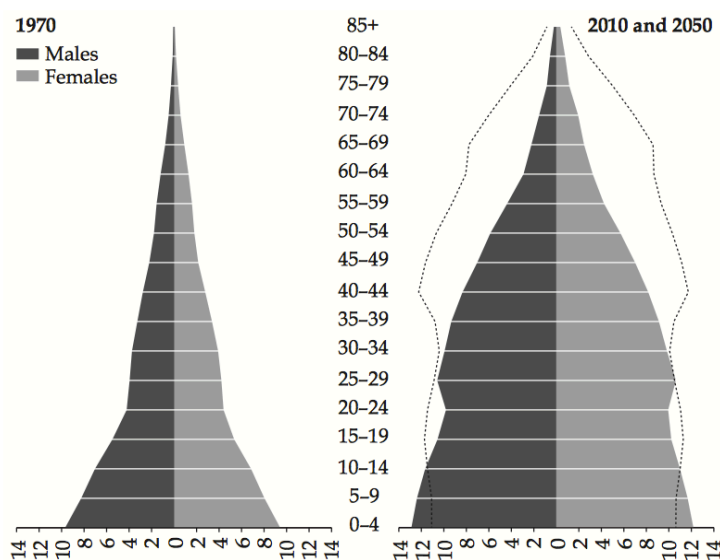


Figure 3-2 Population Pyramid in 1970, 2010 and 2050 (the projection for 2050 is represented by a dashed line).



Table 3-1 depicts selected demographic, health status and economic indicators for Indonesia. The fertility rate has decreased dramatically from 5.7 births per woman in 1960 to 2.5 births per woman in 2000 due to an aggressive family planning campaign that began in the 1980s with a very popular slogan “two children are enough” (Booth, 1992). Furthermore, Indonesia has improved its education system by extending compulsory education from 6 years to 9 years in 1994 and to 12 years in 2016. The adult literacy rate has also increased significantly from 67.3 percent in 1980 to 95.2 percent in 2015.

*Table 3-1 Selected demographic, health status and economic indicators for Indonesia*

<b>Selected Indicators</b>	<b>1960</b>	<b>1970</b>	<b>1980</b>	<b>1990</b>	<b>2000</b>	<b>2010</b>	<b>2015</b>
Population, total (in million)	88	115	147	181	311	242	258
Fertility rate, total (births per woman)	5.7	5.5	4.4	3.1	2.5	2.5	2.4
Life expectancy at birth, total (years)	48.6	54.5	59.6	63.3	66.2	68.2	69
Mortality rate, infant (per 1,000 live births)	148	113	85	62	41	27.5	23
Mortality rate, under-5 (per 1,000 live births)	222	165	120	84	52	33	27
Prevalence of undernourishment (% of population)	n/a	n/a	n/a	n/a	17.8	12.5	7.9
Literacy rate, adult total (% of people ages 15 and above)	n/a	n/a	67.3	81.5	n/a	n/a	95.2
GDP per capita growth (annual %)	n/a	4.7	7.3	5.3	3.5	4.8	3.6
Unemployment, total (% of total labour force) (national estimate)	n/a	n/a	1.7	2.5	6.1	5.6	4.5
Waged and salaried workers, total (% of total employment)	n/a	n/a	n/a	n/a	31.9	36.9	40.2

*Source: World Development Indicators (World Bank, 2018)*

With a GDP per capita annual growth rate of 7.3 percent in 1980, Indonesia used to be one of the fastest growing Asian economies due to the surplus of oil boom in 1980. Compared to the average GDP growth rate in East Asia and the Pacific, excluding high income countries (6%) and LMICs (3.3%) in 1980, Indonesia’s economic growth looked promising. This oil surplus was also invested into the health care system with the development of hundreds of public health centres as a primary contact point for

people to access basic health care services (Booth, 1992). The unemployment rate during the oil boom period was maintained below 3 percent between 1980 and 1990. Unfortunately, the Asian financial crisis in 1997/98 instigated an extreme economic slowdown in Indonesia. Indonesia's currency, the Rupiah, lost 85 percent of its value in 1999 and the inflation rate rose to 78 percent (Suryahadi, Hadiwidjaja and Sumarto, 2012). The unemployment rate escalated to as high as 6.1 percent in 2000 and it never bounced back to its pre-crisis figure. The crisis caused approximately 13.4 million job losses and a rise in the number of poor people from 17 to 40 percent of population (Hopkins, 2006).

The economic crisis did not just leave a long-lasting effect on the Indonesian economy; it triggered massive political unrest culminating in the resignation of President Soeharto in May 1998, 32 years after his inauguration. Soeharto maintained an authoritarian regime with a centralised government aiming to unify a very diverse Indonesia. His fall provided an opportunity to reverse the centralised government with the introduction of Law No. 22/1999, providing more devolved political power to the provinces and districts (Carnegie, 2008). This decentralisation policy also affects the health care system: district health offices have more autonomy in developing health programmes which are responsive to local needs, while the provincial health offices handle cross-district programmes. The central ministry (the Ministry of Health or MoH) is responsible for issuing national guidelines and providing health research and development, but it now relies on the districts to voluntarily report health indicators, creating an incomplete health database (Lieberman, Capuno and Minh, 2005). Decentralisation gives more power to the provinces and districts but the implementation of "big bang" decentralisation in Indonesia has created confusion and overlapping responsibilities between provincial health offices and district health offices, resulting in inefficiencies in carrying out the health programme (Fahlevi and Färber, 2014).

The economic crisis also had a negative impact on the health sector in Indonesia. Increases in the price of drugs and medical supplies reduced people's personal budget share devoted to health (Waters, Saadah and Pradhan, 2003). In addition, the increase in price caused a shortage of drugs and medical supplies in government-run health facilities due to a reduced health budget following a decline in overall

government expenditure (Hotchkiss and Jacobalis, 1999). The utilisation of outpatient care in the past four weeks in both public and private facilities also declined from 8 percent in 1997 to 3.5 percent in 1998 (Waters, Saadah and Pradhan, 2003). Moreover, the economic crisis resulted in psychological distress for the most affected groups, including the less educated, the rural landless and residents in the hardest hit cities (Friedman and Thomas, 2009).

Indonesia's performance in terms of health indicators reveals a mixed picture. On average, Indonesian people in 2015 had a life expectancy of 69 years, higher than the average in LMICs (67.7) but lower than the average for the Southeast Asian countries (72.3). Likewise, mortality rates for infants and children under 5 years shows a similar pattern (The World Bank, 2018). Indonesia had seen an improvement in reducing its maternal mortality ratio (MMR), from 390 in 1994 down to 228 per 100,000 live births in 2007. However, this downward trend has not continued: the most recent estimate reveals an increased ratio, 359 maternal deaths per 100,000 live births in 2012 (BPS Indonesia, 2013, pp.209–215). Despite some technical limitations and wide confidence intervals in MMR calculation (Hill et al., 2006), this non-decreasing trend may prove that Indonesia is still far from reaching its goal to reduce its MMR by 75 percent (Millennium Development Goal) or even to less than 70 per 100,000 live births (Sustainable Development Goal) (United Nations, 2016).

Regional differences are inevitable in Indonesia given its diversity, both culturally and geographically. Most of the western and central regions of Indonesia have Muslim majorities, defined as at least 80 percent of the population identifying as Muslim, whereas all provinces in the eastern region (Maluku, North Maluku, West Papua and Papua) have a 25 percent or larger non-Muslim population. Regarding employment, only Jakarta Special Region and Riau Islands have more than 64 percent of the working age population (15 years and older) employed in the formal sector. By contrast, the remaining provinces have an average of 30 percent, with even lower percentages for the eastern region (BPS Indonesia, 2010). While most provinces have achieved at least 85 percent in terms of the adult literacy rate, a few of the less developed provinces (i.e. West Sulawesi, Nusa Tenggara Islands and Papua) have rates lower than 85 percent (BPS Indonesia, 2010).

The regional differences in health indicators are also quite significant. The eastern region had higher rate of neonatal mortality and under-5 mortality compared to the rest of the provinces in 2012 (BPS Indonesia, 2013) and they are still categorised as an endemic region for Malaria with the Annual Parasite Index (API) score ranging from 4.5 to 42.6 per 1,000 people in 2013 (Johansson Århem et al., 2015).

Furthermore, the eastern region still suffers from some Neglected Tropical Diseases, such as Filariasis (a worm infestation in the lymph vessels) and Yaws (a contagious bacterial infection causing deep ulcers) (Wibawa and Satoto, 2016). In addition, more than 20 percent of children living in West Papua and Papua did not receive any kind of vaccination in 2012 (BPS Indonesia, 2013). Papua lags behind in almost all development indicators which can be attributed to its long history of marginalisation and internal conflicts since its incorporation as a province of Indonesia in 1969 (Widjojo et al., 2008, p.2).

### **Section 3.2 Health expenditure trends**

The amount a country spends on health and the rate at which that spending grows depends on a wide range of social and economic factors, including the financial and organisational structures of a country's health system. There is a strong relationship between the overall income level of a country, usually measured by a country's gross domestic product (GDP), and how much the population of that country will spend on health (World Health Organization, 2014b, pp.4–5). For example, European countries with high incomes (for example, Luxembourg, Switzerland, Norway and Germany) spend more money on health compared to European countries with lower incomes (for example, Romania, Montenegro and Albania) (OECD/EU, 2016). While there is no recommendation on the “right” level of spending on health, increased higher spending is associated with better health outcomes especially for developing countries (World Health Organization, 2014b, p.10).

The trends in health expenditure for Indonesia from 1995 to 2014 are summarised in Table 3-2. Indonesia displays a characteristic typical of developing countries in which private expenditure dominates over public expenditure. Over the span of nearly 20

years, Indonesia has increased its health expenditure (HE) per capita by 3.5 times. Compared to its neighbours, Indonesia's HE per capita is relatively low, as shown in Figure 3-3. Even neighbouring countries with lower GDP, for example Vietnam and The Philippines, have higher HE per capita than Indonesia. Nevertheless, Indonesia's annual growth on health expenditure still demonstrates a positive trend, higher than the average for Southeast Asian countries and mainly after the Asian economic crisis during 1997/98 (see Figure 3-4).

*Table 3-2 Trends in health expenditure (HE) in Indonesia, 1995–2014*

Expenditure	1995	2000	2005	2010	2012	2014
THE* (% of GDP)	1.96	1.98	2.79	2.74	2.90	2.85
THE (nominal term US\$, in billion)	3.95	3.26	7.97	20.07	20.66	20.53
HE per capita in real terms**	85.90	91.04	169.8	227.31	273.83	299.41
			5			
Government HE (% of GDP)	0.71	0.72	0.80	1.03	1.15	1.08
Government HE (% of THE)	36.24	36.63	28.79	37.69	39.61	37.78
Government HE (% of gov't expenditure)	4.93	4.35	4.24	6.12	6.09	5.73
Private HE (% of GDP)	1.25	1.25	1.99	1.71	1.75	1.77
Private HE (% of THE)	63.76	63.37	71.21	62.31	60.39	62.22
External resources for health (% of THE)	1.54	9.04	1.35	1.18	1.08	1.06
Out-of-pocket HE (% of private HE)	72.94	72.66	76.70	75.76	75.09	75.32
Out-of-pocket HE (% of THE)	46.51	46.04	54.62	47.21	45.35	46.87

*\*THE = Total Health Expenditure; \*\*Based on PPP (Purchasing Power Parity)*

*Source: World Development Indicators (World Bank, 2018)*

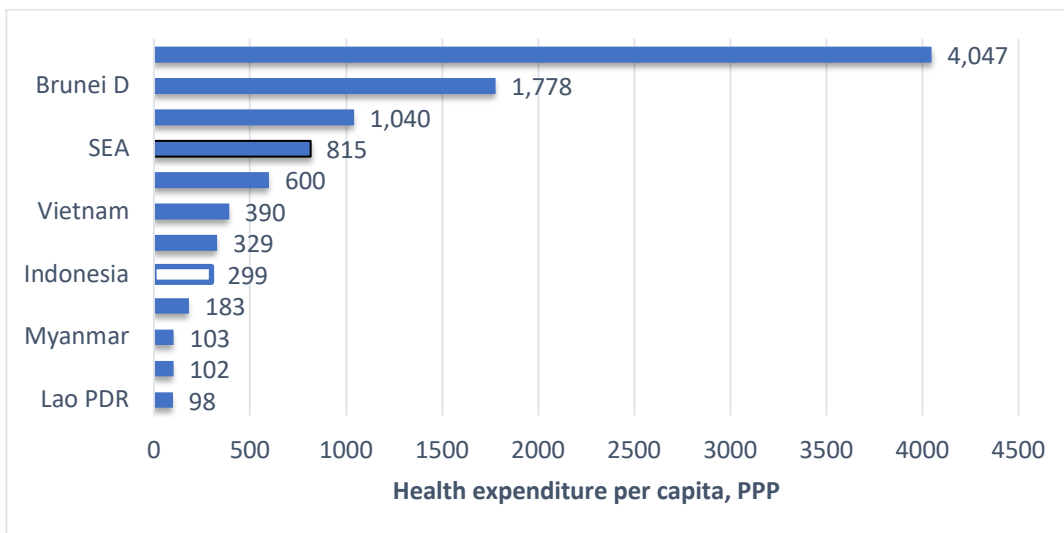


Figure 3-3 Health expenditure per capita converted using 2011 purchasing power rates (PPP), Southeast Asia (SEA) countries in 2014. Source: World Development Indicators (World Bank, 2018)

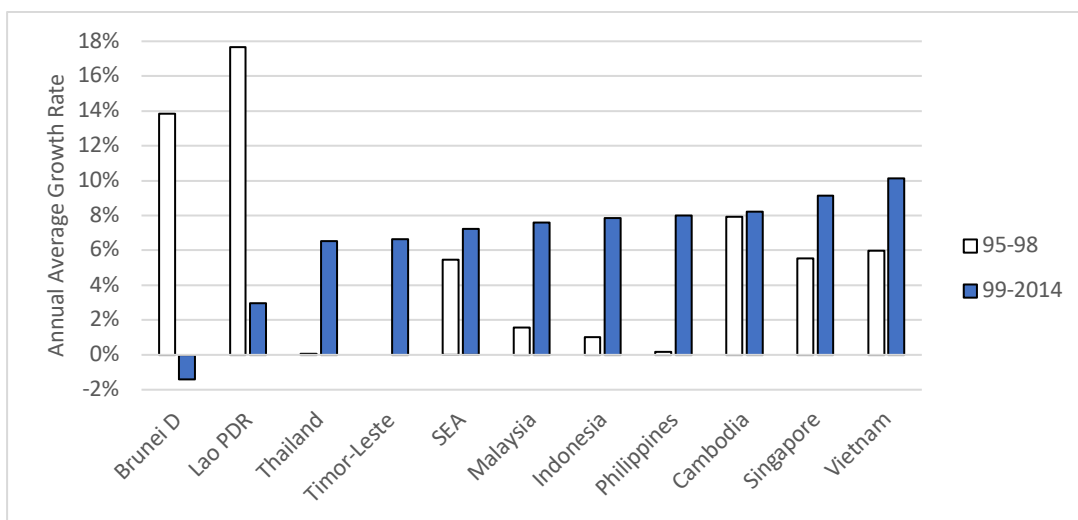


Figure 3-4 Annual average growth rate of health expenditure per capita (in PPP international \$), Southeast Asian (SEA) countries 1995–2014. Source: World Development Indicators (World Bank, 2018)

In terms of total health expenditure (THE) as a share of GDP, Indonesia only allocated 2 to 3 percent of its GDP to the health sector between 1995 and 2014, as shown in Table 3-2. Moreover, the trend for THE as a share of GDP shows an erratic up and down movement despite a continuously positive trend on health expenditure per capita. Higher THE in 2005 and 2012 compared to 2010 might be caused by the introduction of many other social assistance programmes at the same time, which increased overall government expenditure. In fact, all three indicators for government expenditure on health showed an inclining trend from 2005 to 2010 (see

Table 3-2). This suggests that while Indonesia enjoyed strong economic growth after the economic crisis of 1997/98, the health sector was not the top priority in the national budget. For instance, government expenditure on education increased substantially from 1 percent of GDP in 1995 to 3.3 percent of GDP in 2014, whereas government expenditure on health increased only slightly from 0.7 percent in 1995 to 1.1 percent of GDP in 2014 (The World Bank, 2018).

Compared to its neighbours, Indonesia had a lower than average THE as a percentage of GDP in 2014, as shown in Figure 3-5. Moreover, the private sector still dominates total health expenditure, but this is comparable with half of the SEA countries, including Lao PDR, Myanmar, The Philippines, Singapore and Cambodia. However, if we observe government health expenditure as a share of total government expenditure in Figure 3-6, it is clear that Indonesia is lower than the average found in SEA countries, together with other lower-income SEA countries. In its current economic position, Indonesia still has the capacity to put more investment into its health system.

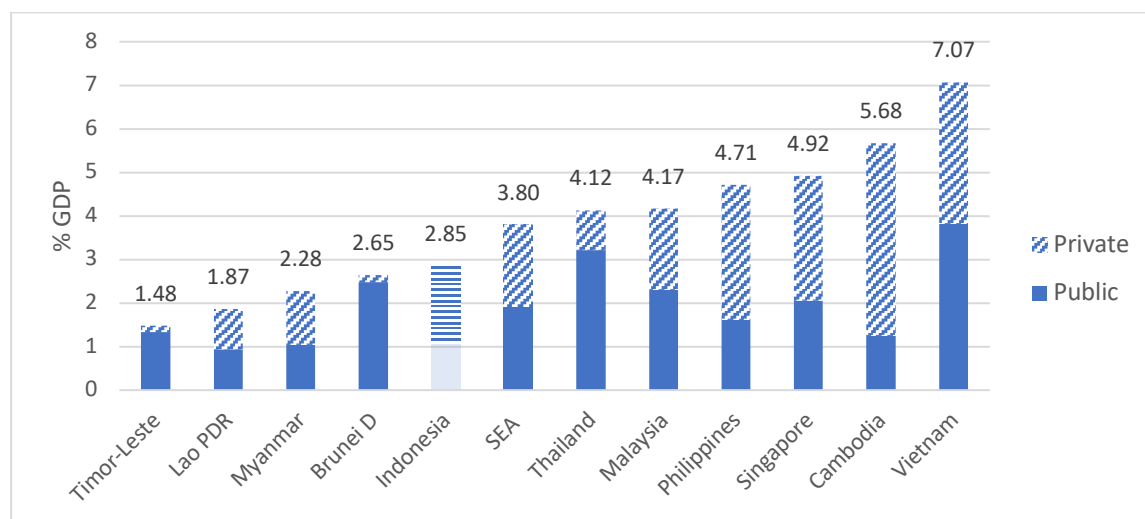


Figure 3-5 Total health expenditure as a % of GDP among Southeast Asian (SEA) countries in 2014. Source: World Development Indicators, The World Bank (2018)

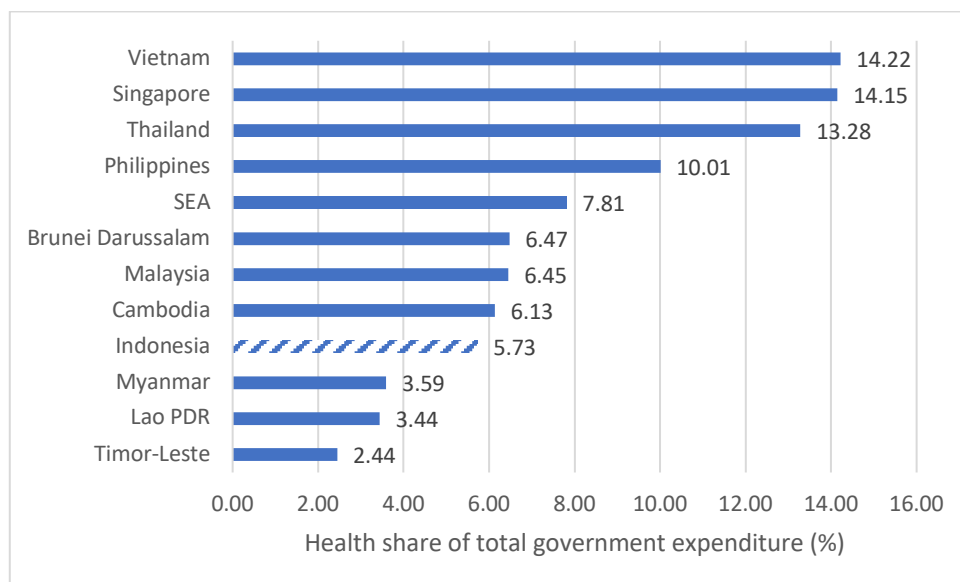


Figure 3-6 Government expenditure on health as a share of total government expenditure, Southeast Asian countries in 2014. Source: World Development Indicators, The World Bank (2018)

The private sector continues to be the dominant source of health care financing, with households' out-of-pocket (OOP) payments accounting for 72–75 percent of private HE between 1995 and 2013. Moreover, the OOP spending share of THE is still relatively high at 46.87 percent in 2014, higher than the average of SEA countries at 40.92 percent (see Figure 3-7). Figure 3-8 presents trends in OOP health expenditure as a percentage of THE, comparing Indonesia with its comparable neighbours in terms of GDP. Overall, there is no clear pattern in OOP trends, but a sharp increase appeared in 2005, the year when the government launched a health insurance scheme for the poor. This sharp increase might be the spillover effect of the unconditional cash transfer (UCT) programme which was launched in the same year. UCT might allow poor people to spend their additional income on accessing private health facilities, which were not previously covered by the health insurance scheme. Furthermore, it is discouraging to see a non-decreasing trend in OOP health expenditure despite the expansion of the public health insurance system over the past 15 years. While Indonesia still fares better than Cambodia and The Philippines, Thailand and Vietnam display stronger progress in decreasing the incidence of OOP health expenditure. Vietnam had a higher OOP share compared to Indonesia in 1995, but has shown a significantly decreasing trend since 2005, outperforming Indonesia since 2010.



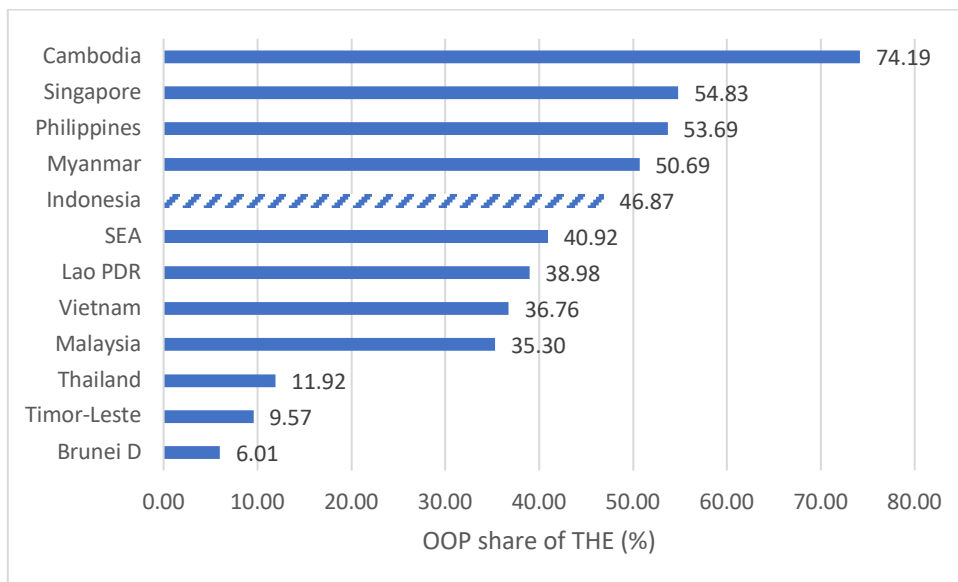


Figure 3-7 Out-of-pocket health expenditure as a % of THE, Southeast Asian (SEA) countries in 2014

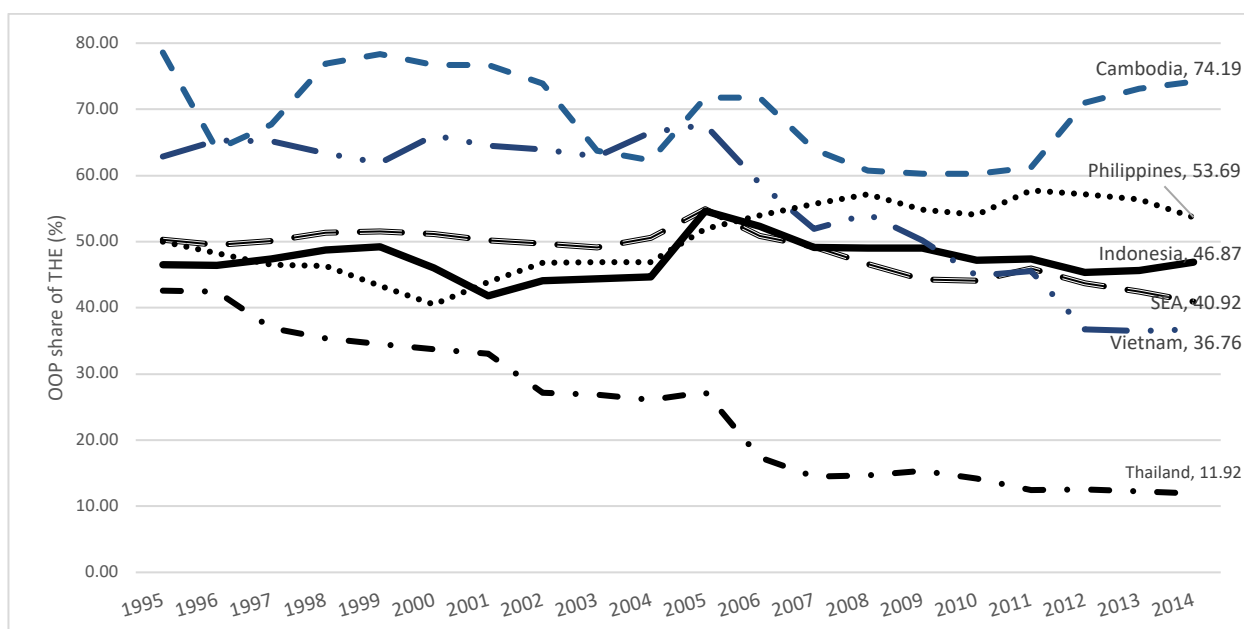


Figure 3-8 Out-of-pocket health expenditure as a % of THE, selected Southeast Asian (SEA) countries from 1995–2014

Source: World Development Indicators, The World Bank (2018)

### Section 3.3 Administrative structure of local government in Indonesia

Before the economic crisis in 1998, Indonesia used to have 27 provinces but the youngest province, East Timor, became an independent nation following the independence referendum in 1999. Moreover, Law No. 22/1999 on Region Decentralisation triggered the development of new provinces and districts. By 2016, there were a total of 34 provinces including 5 special regions: Jakarta as the capital city of Indonesia, Yogyakarta which still recognises the existence of the Javanese monarch as its governor, Aceh which has received special autonomy to implement Islamic sharia law since 2003, and Papua and West Papua both of which receive special autonomy to form a different legislative body representing the indigenous tribes instead of the political parties (BPS Indonesia, 2016).

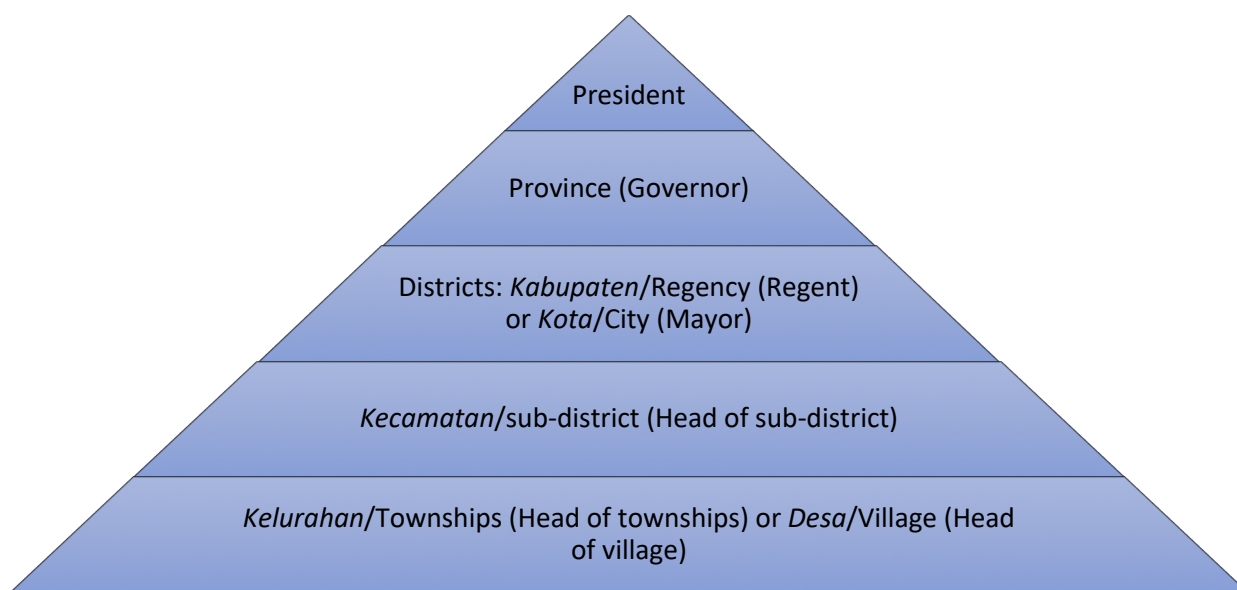


Figure 3-9 Administrative structure of Indonesia (the terms in brackets indicate the leader of the named area)

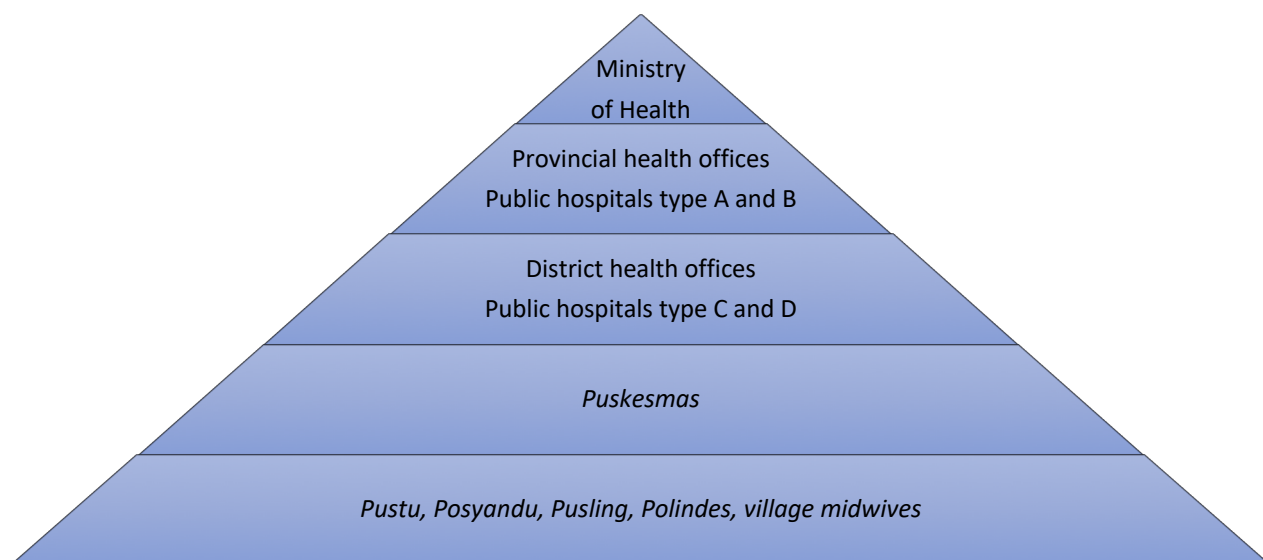


Figure 3-10 Structure of the public-sector health care system in Indonesia

Figure 3-9 summarises the five-tier government hierarchy in Indonesia. Each province is governed by a governor who is directly elected by popular vote of the people. Provinces are further divided into districts. There are two types of district: *kabupaten*/regencies which tend to have larger rural areas and *kota*/cities. The heads of districts (regent/mayor) are also elected by popular vote. Districts have more power in the provision of public services, such as education and public health. They are divided into *kecamatan*/sub-districts and sub-districts are further divided into either *kelurahan*/townships (urban) or *desa*/villages (rural). The heads of sub-districts and townships are appointed by the regents or mayors, but the heads of villages are elected by the popular vote.

Figure 3-10 summarises the management of the public health care system in Indonesia. It almost mimics the structure of government hierarchy in Figure 3-9. Prior to the decentralisation policy in the early 2000s, the decision-making structure for the health sector followed a clear top-down structure with the Ministry of Health (MoH) acting in a very dominant role. However, after the implementation of decentralisation policy, the major decision-making roles were taken over mostly by the district health offices and, to a lesser extent, the provincial health offices (Suwandono et al., 2003). District health offices are accountable to the MoH and local governments (regents/mayors), but they do not answer to provincial health offices.

## Section 3.4 Health service delivery system in Indonesia

The Indonesian health care sectors represent a mix of public and private providers. **Puskesmas (Pusat Kesehatan Masyarakat/community health centre)** is the smallest unit of the publicly-funded health facilities located in a *kecamatan*/sub-district. In 2014, there were 9,671 units of Puskesmas providing primary health care services (for example, polyclinics, child and maternal care, and basic dental services) and health prevention programmes (for example, hygiene, sanitation and health promotion). A Puskesmas is designed to have a doctor, a dentist, nurses, midwives and a public health specialist at the minimum. However, approximately 25 percent of the total number of Puskesmas in rural areas, particularly in the eastern region, have only nurses and midwives providing all Puskesmas programmes (Harimurti et al., 2013). The coverage area of a Puskesmas is determined by the population density, geographical characteristics and the condition of transport infrastructure. A Puskesmas is designed to cover approximately 30,000 people, but in densely populated urban areas it can cover up to 150,000 people.

Table 3-3 Distribution of Puskesmas in Indonesia

	Total Puskesmas	Inpatient and Outpatient	Outpatient Only	Total Puskesmas	Inpatient and Outpatient	Outpatient Only
SUMATERA	1844	490	1354	2477	833	1644
JAVA and BALI	3473	780	2693	3697	1161	2536
NUSA TENGGARA	345	88	257	528	243	285
KALIMANTAN	694	196	498	835	308	527
SULAWESI	814	325	489	1270	544	726
MALUKU and PAPUA	380	131	249	864	232	632
TOTAL	7550	2010	5540	9671	3321	6350

Source:

Historically, the Puskesmas was designed to provide outpatient care only, but some big Puskesmas in urban areas also provide very limited inpatient care that does not require the presence of any specialist doctors. Table 3-3 provides data on the distribution of Puskesmas in the six big islands of Indonesia from 2004 to 2014. In the past decade, the MoH has pushed for the development of more Puskesmas with inpatient care, either by building a new Puskesmas or upgrading the existing ones.

There were 3,321 Puskesmas providing inpatient care in 2014, a 65 percent increase from 2004. In addition to the main Puskesmas in the sub-district, a Puskesmas is also supported by several smaller facilities, such as **Posyandu** (Health and Nutrition Integrated Service Post), **Pustu** (Mini Puskesmas), **Pusling** (Mobile Puskesmas) and **Polindes** (Village Midwives). These supporting facilities aim to expand the main Puskesmas' coverage to more remote areas.

Aside from abundant public facilities, private facilities are also available in many areas of Indonesia. Many of the private practices are public physicians who open a private practice after the close of the Puskesmas' working day (Berman and Cuizon, 2004). Based on data from the 1993 Indonesian Family Life Survey, 80 percent of public sector physicians also work in private practices (Bir and Eggleston, 2003). Patients may prefer to visit a doctor's practice after working hours for convenience and private practices become a suitable alternative for these people. Even though Puskesmas are able to offer cheaper prices and are even free of charge for eligible people, the poorest (especially in urban areas) choose more expensive private providers over Puskesmas care (Bir and Eggleston, 2003).

*Table 3-4 Supporting Facilities for Puskesmas in Indonesia*

<b>Facilities</b>	<b>Number (Year)</b>	<b>Coverage</b>	<b>Services</b>
Puskesmas	9,671 (2014)	30,000 – 150,000	Basic health care services, child and maternal care, family planning, sanitation, health prevention and promotion
Pustu	23,875 (2013)	2,500 – 10,000	An extension of Puskesmas to reach villages, but with more limited facilities
Posyandu	280,225 (2013)	50 children under 5-years of age and their mothers	Family planning, maternal care, child nutrition (e.g. growth monitoring, supplemental feeding), immunisation
Pusling	8,009 (Four-wheels) 958 (Boats) (2013)	Access to more remote areas; Either by four-wheel vehicle or boat	Basic health care services, immunisation, family planning
Polindes	42,656 (2013)	One village	Maternal care, promotion and preventive health services

*Source: Indonesia health system review (Mahendradhata et al., 2017)*

The MoH uses public hospitals to provide secondary care and the referral facilities for the Puskesmas. There were 2,228 hospitals in 2013; 70 percent of them were publicly funded. Public hospitals in Indonesia can be categorised into four types, with type A as the highest and type D as the lowest (Mahendradhata et al., 2017).

According to the regulations, hospital categorisation is based on facilities and the number of specialised types of care provided by the hospitals (see Table 3-5 for more detail). Hospital types A and B typically cover the area of a province, whereas types C and D only cover a district or lower. There is also a specialist hospital which can provide only one or two types of specialised care. One of the most popular specialist hospitals is the Maternal and Child Hospital (RSIA/*Rumah Sakit Ibu dan Anak*) that provides paediatrics, and obstetrics and gynaecology services. There were 503 units of specialty hospitals in 2013: 32 percent of them were RSIA and 19 percent were obstetrics hospitals only.

Table 3-5 Public hospital type in Indonesia based on Permenkes No. 340/menkes/per/III/2010

Hospital type	Basic specialist care*	Supportive specialist care**	Other specialist care†	Subspecialist care††	Number of beds (minimum)
A	4	5	12	13	400
B	4	4	8	2	200
C	4	4	0	0	100
D	2	0	0	0	50

\* Basic specialist care: Internal medicine, general surgery, paediatrics and obstetrics & gynaecology

\*\* Supportive specialists care: Anaesthesiology, radiology, medic rehabilitation, clinical pathology and anatomical pathology

† Other specialists care: Ophthalmology, Ears, Nose and Throat (ENT), neurology, cardiology, dermatovenereology, psychiatry, respiratory, orthopaedic, urology, neurosurgery, plastic surgery and forensic medicine.

†† Subspecialists care: Any subspecialist care from either basic or other specialists care

In addition to the different types of hospital, there are also several classes of inpatient ward in each hospital namely VIP, first, second and third class. The MoH does not issue a specific regulation in determining the classes of inpatient wards, meaning that the standard of the third-class inpatient wards can differ from one hospital to another. Nevertheless, the third-class inpatient ward is always the lowest class in which patients have to share the ward with four to six patients and only the VIP class can allow one patient per room. The difference in inpatient ward classes mostly determines the amount of non-medical facilities, but all patients should receive a

similar quality of medical service regardless of the class. This inpatient ward division is important in determining the amount of contribution under the JKN scheme which will be explained in the next section.

The health care supply in Indonesia has two main problems. Firstly, Indonesia has relatively low hospital density and uneven distribution across the country. In 2013, its ratio of hospital beds was only 0.93 per 1,000 people, which is very low compared to neighbouring countries such as Thailand, The Philippines and Vietnam (see Figure 3-11).

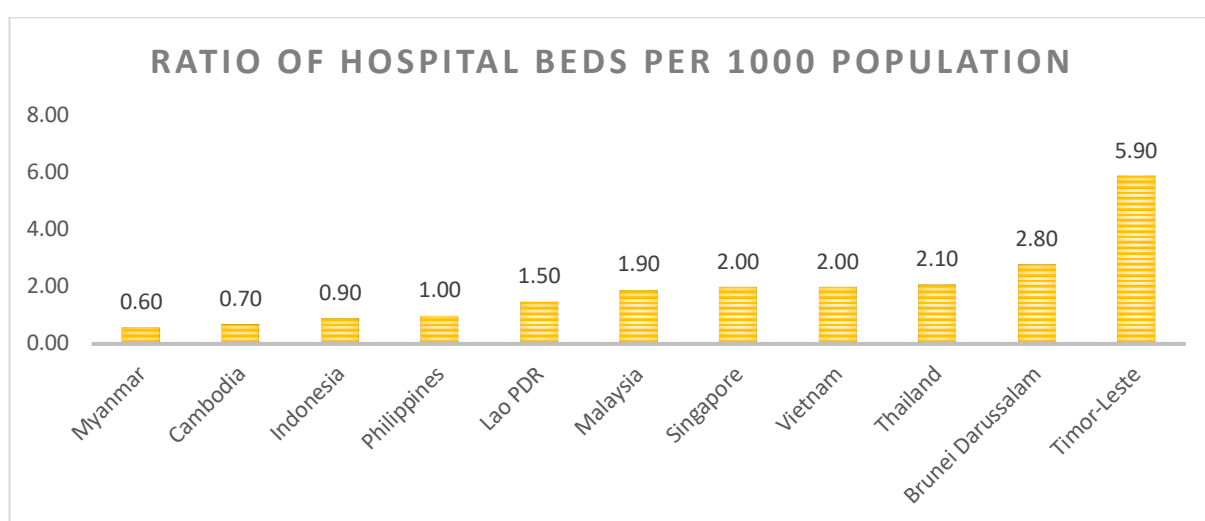


Figure 3-11 Ratio of hospital beds in Southeast Asian countries (World Bank, 2014)

Table 3-6 provides the distribution of physicians and hospital beds across all 34 provinces. The ratio of hospital beds does not fully reflect the variation in area coverage or the population density in any given area. Based on the unadjusted ratio, West Papua and Maluku have a higher ratio compared to the national average (0.93). While both provinces may have, on average, one hospital bed per 1,000 population, the coverage of one bed spans a much wider area compared to provinces that have denser populations, for example, West Java or West Sumatra. I therefore use the

inverse of the share of the province size, defined as  $[\text{province size}/\text{total Indonesia size}] \times 100\%$ , as a multiplier to adjust the ratio. This adjustment factor will give more weighting for provinces with a large area. Based on this adjustment, both provinces have a much lower ratio while DKI Jakarta, as the capital city region, has the highest ratio. DKI Jakarta has the fourth largest number of beds but its area size is the smallest compared to the other provinces. The adjusted ratio provides stronger evidence of the uneven distribution of health facilities in Indonesia.

Secondly, Indonesia also has a relatively low density of health providers, especially physicians and dentists, and they are further concentrated in more developed areas. As shown in **Error! Reference source not found.**, the density of physicians is relatively low compared to neighbouring countries in Southeast Asia. The same problem occurs with the ratio of hospital beds: simply dividing the number of physicians by the number of populations does not reveal the geographical variation among the provinces. DKI Jakarta, which is the most developed area and the capital city of Indonesia, has the same unadjusted ratio as Maluku, one of the underdeveloped provinces in the eastern region with many small islands. According to the unadjusted ratio, Maluku has more than one doctor per 1,000 population, but their doctor has to cover larger area than their counterpart in Jakarta. If the ratio is adjusted to control for geographical variation, Jakarta has the highest density of physicians compared to the others and Maluku has a much smaller density compared to the national average.

*Table 3-6 Distribution of physicians and hospital beds before and after adjustment*

Province	Ratio of hospital bed	Adjusted ratio of hospital bed	Density of Physician	Adjusted Density of Physician
Aceh	1.12	0.37	0.31	0.10
North Sumatera	1.36	0.36	0.23	0.06
West Sumatera	1.08	0.49	0.34	0.16
Riau	0.83	0.18	0.19	0.04
Jambi	0.84	0.32	0.21	0.08
South Sumatera	0.69	0.14	0.14	0.03
Bengkulu	0.91	0.87	0.24	0.23
Lampung	0.51	0.28	0.13	0.07



Bangka Belitung Islands	0.84	0.98	0.25	0.29
Riau Islands	1.04	2.42	0.29	0.68
DKI Jakarta	1.99	57.30	0.26	7.56
West Java	0.62	0.33	0.10	0.05
Central Java	0.96	0.56	0.14	0.08
Yogyakarta	2.85	17.35	0.41	2.51
East Java	0.83	0.33	0.11	0.05
Banten	0.55	1.09	0.11	0.23
Bali	1.20	3.98	0.25	0.83
West Nusa Tenggara	0.47	0.49	0.12	0.12
East Nusa Tenggara	0.74	0.29	0.12	0.05
West Kalimantan	0.93	0.12	0.13	0.02
Central Kalimantan	0.70	0.09	0.20	0.03
South Kalimantan	1.00	0.50	0.20	0.10
East Kalimantan	1.38	0.20	0.23	0.03
North Kalimantan	-	-	0.40	0.10
North Sulawesi	1.83	2.53	0.43	0.59
Central Sulawesi	0.99	0.30	0.19	0.06
South Sulawesi	1.18	0.48	0.17	0.07
Southeast Sulawesi	0.80	0.40	0.19	0.09
Gorontalo	0.90	1.53	0.25	0.42
West Sulawesi	0.57	0.65	0.19	0.21
Maluku	1.32	0.54	0.24	0.10
North Maluku	1.07	0.64	0.27	0.16
West Papua	1.23	0.07	0.27	0.02
Papua	0.88	0.17	0.22	0.04
<b>National Average</b>	<b>0.93</b>		<b>0.16</b>	

## Section 3.5 The health financing system in Indonesia

Indonesia has a long history of experimenting with various health financing strategies, from community-based health insurance (CBHI) in earlier years to social health insurance today. The history of the health financing system in Indonesia will be explained in five sections: section 3.5.1 presents Indonesia's attempt to establish CBHI to support poor people; section 3.5.2 provides a brief history of the expansion of the private health insurance market in Indonesia; section 3.5.3 explains the social security net in response to the Asian economic crisis in 1997/98; section 3.5.4 gives a brief history of the foundation of national health insurance; and lastly section 3.5.5

describes the most current public health insurance scheme, the JKN programme, in more detail.

### 3.5.1 Community-based health insurance

In early 1970, Indonesia attempted to introduce a programme of community-based health insurance (CBHI) which was called *Dana Sehat/Healthy Funds* (Saludung, 1997). This programme aimed to cover the rural population who needed financial assistance to access health care services. The exact coverage rate was unclear due to conflicting reports from different sources (Thabrany, 2012; Hsiao, 2004; Saludung, 1997). The local community was involved in deciding on the benefits of being a member. The premium of most healthy funds was relatively affordable, 0.5 percent of household income on average (Nugroho and Elliott, 1977), yet too low to generate adequate risk pooling. With no subsidy from the government, this low amount of contribution led to limited benefits which could only cover basic health services from the Puskesmas. In addition, many small-sized Healthy Funds in the villages did not have the capacity and experience in insurance management and, therefore, could not expand the pooling and manage the fund efficiently. A fee-for service system instead of prepayment was the main reimbursement mechanism indicating a lack of cost control (Hsiao, 2004). The dropout rate after the first year was 60 to 70 percent because ex-members perceived that joining the scheme was not worth the money anymore.

Table 3-7 Timeline of Health Care Reform in Indonesia

Year	Reform
1968	<b>Askes</b> , the first health insurance scheme for civil servants. Also, <b>Taspen</b> for pensioners in the public sector and <b>Asabri</b> for the armed forces and police
1970	<b>Dana Sehat</b> (Health Fund) was first introduced. Similar to community-based health insurance
1978	<b>Astek</b> (Social security for private labour) was first introduced, only covered workplaces > 500 employees
1992	Astek was reformed into <b>Jamsostek</b> , now covered workplaces > 100 employees

1992	<b>JPKM</b> (similar to HMO in the USA) was first introduced
1996	<b>Kartu Sehat</b> (Health Card) was first introduced to provide subsidised health care to the poor
1998	<b>JPS</b> (Social Safety Net) in response to the financial crisis with the help of an ADB loan; re-introduced the Health Card programme
2004	<b>JPKM</b> and <b>Healthy Fund</b> were no longer supported due to their failure in expanding its coverage
2004	National Social Health Insurance ( <b>SJSN</b> ) Act was enacted
2005	<b>Askeskin</b> (Health Insurance for Poor Population) was first established; managed by PT Askes
2008	Askeskin was transformed into <b>Jamkesmas</b> and managed by the MoH
2011	Social Security Administrator Agency ( <b>BPJS</b> ) Act was enacted following lawsuits from labour unions
2014	Askes, Jamsostek and Jamkesmas were unified under one agency, <b>BPJS-Kesehatan</b> . The unified scheme is called Jaminan Kesehatan Nasional ( <b>JKN</b> )/National Health Insurance

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*Sources:* (Hsiao, 2004; Thabrany and Mundiharno, 2012; Thabrany, 2012; Mahendradhata et al., 2017)

### 3.5.2 Expansion of the private insurance market

Recognising the failure of Healthy Funds to expand more widely, the government introduced several health financing reforms in the early 1990s that favoured the growth of the private insurance system. In 1992, the government ratified Law No. 3/1992 on the re-introduction of a social security scheme named **Jamsostek** that expanded the coverage for employees in the formal sectors, excluding civil servants. Furthermore, the government reformed the health insurance scheme for civil servants by changing the status of its management from a government agency to a state-owned company, which was called **PT Askes**, with higher autonomous status. More importantly, the government also issued Law No. 2/1992 on the regulation of the insurance market which permitted private insurance companies to sell health insurance products, regulated and supervised by the Ministry of Finance. To stimulate the growth of the private health insurance market, the government also allowed the employers to opt out from the Jamsostek membership if they could purchase a better health insurance plan from private plans and permitted PT Askes to sell commercial health insurance products to non-civil servants. By 1997, an

estimated 1.6 million persons were covered by commercial indemnity health policies, up from 450,000 in 1993 (Lieberman and Marzoeki, 2002).

Lastly, under Law No. 23/1992 the MoH actively promoted the managed care model to reduce government expenditure on the health care system. *Jaminan Pemeliharaan Kesehatan Masyarakat (JPKM)* (Community Health Maintenance Organisation) is Indonesia's interpretation of the Health Maintenance Organisation (HMO) model, which was very popular in the USA in the 1990s prior to its downfall in the early 2000s (Mechanic, 2004). The MoH as the licensor would give the JPKM license to private businesses willing to adopt the managed care model and become the **Bapel**, an acronym for *Badan Penyelenggara/Executing Agency*. Thabrany (2003) argued that JPKM's failure to expand its membership and provide adequate financial protection was due to the low technical capacity of the MoH to regulate and supervise the conduct of health insurance businesses; the MoH did not even consider JPKM as part of the health insurance product. JPKM still had to compete with other private plans, but it had two disadvantages. Firstly, Indonesian people did not have much experience in understanding the risk transfer mechanisms in insurance or managed care. Secondly, the managed care required its members to utilise the contracted providers only, whereas other private plans could offer a wider selection of providers (Marzolf, 2002, p.20). Today, the MoH has stopped providing new JPKM licenses.

### 3.5.3 Social security net post the economic crisis 1997/1998

In 1998, the government received a big loan from the Asian Development Bank (ADB) to alleviate the impact of the Asian economic crisis in 1997/1998. The government introduced a range of safety net programmes in key sectors, such as food, education and health. For the health sector, the government re-introduced the *Kartu Sehat/Health Card* programme. It was first launched in 1996 but it failed to reach its target population due to poor management at Puskesmas level. This programme was targeted towards the population most vulnerable to economic shocks. The targeting strategy utilised a combination of geographic and community-based targeting instruments, mostly based on the outdated database from the National Family Program Coordinating Agency (BKKBN). Furthermore, district health officials and

community members created additional criteria based on local needs (Sparrow, Suryahadi and Widyanti, 2013). The Health Card programme paid health facilities Rp 10,000 (50 pennies) per year per person. It only permitted the beneficiaries to utilise public health care providers to seek medical treatment (Hsiao et al., 2007).

In the end, this programme just operated as a price subsidy programme for accessing public health care facilities with less attention to expanding its coverage. Johar (2009) evaluated the Health Card programme by analysing panel data from the Indonesia Family Life Survey (IFLS) 1, 2 and 3 (1993, 1997, and 2000). She argued that this programme had little or no effect on the utilisation of health care explained by its inelastic demand (Johar, 2009). The lack of other incentives on the demand side, compounded by the inadequate supply of the public health system, meant that the Health Card programme had little power to increase utilisation. In a different paper, she also asserted that the Health Card programme further reduced the quality of public health centres in rural areas by reducing health workers' commitment to public jobs (Johar, 2010). Since they received a fixed capitated income from the Health Card programme, they sought additional income by opening private practices outside of working hours.

#### 3.5.4 **Moving towards a unified social security system in Indonesia**

Meanwhile, the government realised that the Health Card programme was not sufficient to support the health system in the long run. The government passed the **SJSN Law No. 40/2004** as the first law regulating the establishment of the Social Security System in Indonesia. Due to the gridlock of political debate in legislative bodies, the government rebranded the Health Card program into a new programme called **Askeskin** (Asuransi Kesehatan Miskin/Health Insurance for the Poor) as a temporary measure to partially address the SJSN law. However, some regarded this attempt as a justification for the reduction of the fuel subsidy at the beginning of 2005 (OECD, 2010). The Askeskin programme was administered by PT Askes, the state-owned company responsible for managing the health insurance scheme for the civil servants. The Askeskin programme was funded by general tax revenue, initially by the surplus from the reduction of fuel subsidy. It targeted only the poor population identified a priori based on various means-tested criteria. Statistics Indonesia (BPS)

was responsible for supplying the updated database on the poor population in Indonesia, replacing the outdated version held by BKKBN used for distributing the Health Card programme in 1998. It was targeted to cover 60 million people, which made it the biggest health insurance provider in Indonesia.

Another improvement of the Askeskin programme in comparison to the Health Card was the expansion of the benefits on offer. It included more specialist services through a larger network of private practices and hospitals. In addition, while the Health Card programme used a capitation strategy to contain the cost, Askeskin reimbursed the full cost of services delivered in both public and private health care facilities (i.e. fee-for-service). While the doctor received more compensation in delivering services for Askeskin patients compared to the Health Card, the reimbursement of the costs was often delayed for months. Despite the problems with its implementation, Askeskin was considered to be successful in increasing the utilisation of outpatient care (Sparrow, Suryahadi and Widyanti, 2013) but there is inconclusive evidence about whether it provided adequate financial protection to its enrollees (Sparrow, Suryahadi and Widyanti, 2013; Aji et al., 2013).

In 2008, the government reformed Askeskin into a new programme called Jamkesmas/Community Health Insurance. The MoH took over the management of Jamkesmas from PT Askes, who had previously managed Askeskin. One of the aims of this reform was to address the many complaints from hospitals in terms of the delays in reimbursement (Aji et al., 2013). Following government mandates, Jamkesmas expanded the target population to include not only the poor population, but also the near poor population. In 2012, Jamkesmas covered 76.4 million people, 32 percent of the total population. Beneficiaries were identified by a combination of means testing, conducted by Statistics Indonesia (BPS), and local eligibility criteria. BPS issued a quota of Jamkesmas members per district and the district had the power to alter the quota based on their own criteria. One critical problem in the enrolment process was the poor distribution of membership cards. Harimurti *et al.* (2013) reported that after matching the number of poor people who had Jamkesmas cards and the number of Jamkesmas cardholders who were actually poor, there was an indication of a leakage rate of 52.4 percent. In one local survey by IBP Indonesia, the utilisation of the Jamkesmas quota by local officials to distribute the Jamkesmas card varied greatly from 57 percent to 99 percent (Dwicaksono, Nurman and Prasetya, 2012).

Central government realised that the Jamkesmas programme would not cover all of the people who needed medical treatment but were not eligible to receive Jamkesmas. Therefore, they also mandated district and provincial governments to initiate local schemes which would adopt a similar principle to Jamkesmas in order to cover the uninsured population who were not eligible for Jamkesmas. These local initiatives are jointly called **Jaminan Kesehatan Daerah/Jamkesda** (Local Health Insurance). In 2011, approximately 32 million people were covered by Jamkesda in 367 districts (Thabrany and Mundiharno, 2012, p.48). The evaluation of Jamkesda has proven difficult due to the heterogeneity of the schemes' designs, including benefits structure, provider payment systems and eligibility criteria. While all Jamkesda schemes included allocations from the local budgets, a few required payments from beneficiaries or offered only limited benefits according to income (Aspinall, 2014; Tangcharoensathien et al., 2011).

### 3.5.5 JKN programme for all

The discussion in the previous section has shown that health financing in Indonesia was fragmented on the basis of job sector. Government employees were covered by Askes and employees in the formal sector were covered by Jamsostek or private insurance. Unemployed people and workers in the informal sector could be covered by either Jamkesmas if they were eligible or Jamkesda if it was available in their district/province; the rest were uninsured. However, beginning on the 1 January 2014, most of these different schemes have been unified under one scheme called **Jaminan Kesehatan Nasional (JKN)**/ National Health Insurance programme managed by a semi-independent agency named **Badan Pengelola Jaminan Sosial – Kesehatan (BPJS-K)**/Social Security Administration Agency – Health. According to Table 3-8, it is estimated that 88 million people (37 percent) were still uninsured in 2012. Jamsostek only represented 2.3 percent of the population even after 20 years of its implementation. The JKN programme was introduced to address the gaps in health insurance coverage in Indonesia. In this thesis, the JKN programme will be the main programme of interest.

Table 3-8 Health insurance coverage in Indonesia, 2012

Type of health insurance	Total (in millions)	Percentage
Askes for Civil Servants	17.3	7.2%
Askes for Military/Police	2.2	0.9%
Jamkesmas	76.4	31.9%
Jamsostek	5.6	2.3%
Jamkesda	31.8	13.3%
Private insurance	15.4	6.4%
Askes (private plan)	2.9	1.2%
Total Insured	151.5	63.2%
Total Uninsured	88.1	36.8%
Total Population	239.7	100.0%

Source: Peta Jalan JKN 2014-2019 (Thabrany and Mundiharno, 2012)

Reiterating the discussion in the previous sub-section, the basis of the JKN programme originated from the SJSN Law No. 40/2004. Based on this law, the central



government launched a new scheme called Askeskin targeting the poor population, reformed it into Jamkesmas in 2008 with an expanded target population and new management, and mandated local governments to initiate Jamkesda in order to cover people who were ineligible for Jamkesmas. The law also dictated that it was necessary to create a semi-independent agency to manage the health insurance for all citizens, but it took seven years for the Indonesian parliament to ratify the BPJS law to establish the Social Security Administration Agency/BPJS in October 2011. This delay was driven by a change in the political regime that occurred soon after the SJSN law's enactment in 2004 (Kwon and Kim, 2015) and heavy resistance from Askes, Jamsostek and lobbyists from private health insurance companies (Aspinall, 2014).

Table 3-9 Monthly contribution for each type of JKN member as of January 2016\*

	Premium	Paid by	Benefit (inpatient ward) <sup>†</sup>
1. Penerima Bantuan Iuran (PBI) /Contribution Assistance Recipients	Jan 2014 – Mar 2016: IDR 19,225		3 <sup>rd</sup> class
2. Veterans and their dependants	2.25% of third-grade civil servants' basic payroll*		1 <sup>st</sup> class
3. Peserta Pekerja Penerima Upah (PPU)/ Salaried workers including their dependants (max 4):			
3a. Government employees (including civil servants, military and police officers)	5%	3% employer 2% employee	Grades 1-2: 2 <sup>nd</sup> class Grade 3 and above: 1 <sup>st</sup> class
3b. Government employees in state-owned companies and private employees	5%	4% employer 1% employee	Salary up to 1.5 times non-taxable income: 2 <sup>nd</sup> class Salary 1.5-2 times non-taxable income: 1 <sup>st</sup> class
3c. Extra dependant (fourth child and more, parent and parent-in-law)	1% per person	Employee	Follow 3a or 3b
4. Non-salaried workers (PBPU) and Non-workers including their family members	IDR 25,500 for 3 <sup>rd</sup> class IDR 42,500 for 2 <sup>nd</sup> class IDR 59,500 for 1 <sup>st</sup> class		According to the premium

Source: Official BPJS-K website: <https://bpjs-kesehatan.go.id> (available in English).

\* Starting from March 2016, the contribution paid by the government for PBI beneficiaries has increased to IDR 23,000. The contribution for PBPU/non-salaried workers and non-workers increased to IDR 30,000, IDR 51,000, and IDR 80,000 respectively from 3<sup>rd</sup> class to 1<sup>st</sup> class.

† Inpatient ward can be classified into VIP class, 1<sup>st</sup> class, 2<sup>nd</sup> class and 3<sup>rd</sup> class (the lowest). JKN does not cover VIP class which allows the patient to not share a ward with other patients. If the patients want to upgrade their class, they have to pay the bill's difference between their current class and the upgraded class.

Under the BPJS law, BPJS is divided into two separate bodies: one for health and another one for pensions. BPJS-Kesehatan/BPJS-Health is the main actor for

administering the JKN programme. BPJS-K have two types of goal: a key goal and several intermediate goals. The key goal is to achieve universal health coverage by 2019. The main intermediate goal is to unify the management of Askes, Jamsostek and Jamkesmas under one single payer system; approximately 121.6 million people (Thabrany and Mundiharno, 2012).

For this new scheme, Indonesia has adopted a social health insurance model with two distinct characteristics: the informal workers are allowed to contribute to the same pool as the formal workers and the government pays the contribution for the most vulnerable population. Table 3-9 provides the details of the contribution schedule for different groups of members. In general, there are two big groups: (1) the subsidised group or *Penerima Bantuan Iuran (PBI)/Contribution Assistance Recipients* including the poor population and totally disabled individuals whose contributions are paid for by the government, and (2) the contributory group which consists of *Peserta Pekerja Penerima Upah (PPU)* /salaried employees (government and private) and their dependants, *Peserta Pekerja Bukan Penerima Upah (PBPU)/non-salaried workers*, and *Peserta Bukan Pekerja/non-workers* (see Table 3-9 for more detail). To minimise fraudulent membership, late payment is penalised with a membership deactivation. Members who re-activate their membership and use JKN to pay any inpatient care services within 45 days after the first day of re-activation must pay a certain amount of fine, capped at 30 million rupiahs (8.5 times the regional minimum monthly wage in Jakarta) (Kesehatan, 2017). Based on Table 3-10, JKN had covered 195 million people or 76 percent of the total population by April 2018. Assuming private insurance and Askes private plans grow at a constant rate, the uninsured population has decreased from 36.8 percent in 2012 to 14.4 percent in 2018. In addition, JKN has attracted 32 million workers in the informal sector and unemployed people who might not have had any insurance before the introduction of the JKN programme.

Table 3-10 JKN members, based on type of membership as of 1 April 2018

Type of members	Number of members	Proportion
1. The subsidised group = PBI	116,982,202	59.9%
2. The contributory group = PPU + PBPU		
2a. Civil servants, military, and police officers	16,849,975	8.6%
2b. Private and state-owned companies	29,235,691	15.0%
2c. Non-salaried workers and non-workers	32,102,415	16.4%
Total	195,170,283	100%

Source: Official website of BPJS-K. Accessed at 9 April 2018. <https://bpjskesehatan.go.id/bpjs/index.php/jumlahPeserta>

In terms of benefits packages, JKN offers comprehensive benefits packages, covering outpatient and inpatient care at primary level up to tertiary hospital level, with the exclusion of a few types of care. The JKN does not cover: (i) services that are not in accordance with protocols; (ii) materials, tools or procedures for cosmetic purposes; (iii) general check-ups; (iv) prosthetic dental care; (v) alternative therapy (for example, acupuncture, traditional healers); and (vi) in vitro fertilization and infertility programmes including treatment for impotence (Mahendradhata et al., 2017, p.81). This represents quite a bold move for Indonesia considering some countries that have achieved UHC at an earlier stage (e.g. Thailand and Rwanda) tend to exclude some of the very costly treatments, such as renal dialysis and expensive cancer treatment (Yiengprugsawan et al., 2010). In addition, under JKN regulations, cost-sharing is not allowed, unless the beneficiaries want to upgrade to a higher level of hospital ward class which will provide them with better non-medical facilities but similar medical treatment. This very generous benefit with no cost-sharing increases the overall health budget and threatens the sustainability of the JKN programme in the long run.

Beneficiaries can seek treatment in the registered facilities set by the BPJS. This consists of all government-owned health facilities and contracted private health facilities. BPJS pays primary health facilities prospectively through capitation and diagnosis related groups using the Indonesian definitions (INA-CBG) for hospital services. The monthly capitation is determined by the number of registered enrollees in the health facilities. INA-CBG price schedules are negotiated with the hospital associations. The hospital bills are determined by INA-CBG codes, the case-mix index

in the hospital, the regional location of the hospital and the type of hospital (i.e. type A – D) (Kesehatan, 2017).

### **Section 3.6 Summary**

This chapter has provided an overview of the demographic, economic and health indicators of Indonesia and has compared the health expenditure indicators with other Southeast Asian (SEA) countries. Despite its moderate recovery from the economic crisis two decades ago, Indonesia has not invested adequate resources into health care: less than 3 percent of its GDP was devoted to health in 2012, which is lower than the average for the SEA countries. Moreover, 45 percent of the total health expenditure comes from the private sector, of which 75 percent comes from out-of-pocket payments. This has provided a strong argument for the government to establish a national health insurance programme in order to remove the barriers to utilising medical care and protect people from financial distress due to medical care consumption.

The establishment of the JKN programme in 2014 demonstrates good, albeit slow, progress by the government in ensuring access to health insurance for everyone. It has accumulated a big proportion of enrollees from existing public health insurance, i.e. civil servants (Askes), formal workers (Jamsostek) and poor people (Jamkesmas and Jamkesda), as well as people who were previously uninsured prior to 2014. Due to its generous medical benefits, it is expected that we will see a significant impact on utilisation and out-of-pocket health expenditure, but this may not be the case if we look at other countries' experiences, for example, China (Wagstaff and Lindelow, 2008). In the next chapter, I will review the evidence on whether health insurance has any impact on access to care, financial protection and health status.

# **Chapter 4 Review of systematic review of the impact of health insurance on access to care, financial protection, and health status**

## **Section 4.1 Introduction**

Many low- and middle- income countries (LMICs) have introduced health insurance programmes in the last few decades (World Health Organization, 2014a). A number of systematic reviews have been undertaken over the years to understand and synthesise the impact of health insurance on access to care, financial protection, and health status (Acharya et al., 2013; Giedion et al., 2013; Spaan et al., 2012; Ekman, 2004). These reviews differ in their focus and approach and do not always include the same studies within the same period. Moreover, there is also some concern about variation in the quality of systematic reviews which is important to overcome two biases: selection bias which may be inherent from the primary studies, and reporting bias from the process of the review itself (Moher et al., 2002). It is therefore useful to synthesise the large body of evidence on health insurance in LMICs. The aim of this chapter is to conduct a review of systematic reviews on publicly-financed health insurance programmes in LMICs, taking account of the methodological quality of systematic reviews and to explore the impact evaluation methodology from the available evidence.

## **Section 4.2 Methods**

### **4.2.1 Selection of studies**

In this review of reviews, I included studies that met the following four characteristics of a systematic review, according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) definition (Moher et al., 2015):

- (a) A clearly stated set of objectives with an explicit, reproducible methodology;
- (b) A systematic search that attempts to identify all studies that would meet the eligibility criteria;
- (c) Assessment of the validity of the findings of the included studies (e.g., assessment of risk of bias and confidence in cumulative estimates); and

- (d) Systematic presentation and synthesis of the characteristics and findings of the included studies.

Some other non-systematic reviews also exist and could provide additional insight into the overview questions. However, it is difficult to assess their qualities because they do not follow a standardised review method hence their exclusion from this review.

#### 4.2.2 **Types of participants**

This review of reviews included only reviews that focus on LMICs as determined by per capita gross national income (GNI) estimated using the World Bank Atlas method (World Bank, 2016). Despite the problems associated with the income indicator and the way groups are classified (Alonso, Cortez and Klasen, 2014), this classification has been used for many systematic reviews in health sciences (e.g. Eaton et al., 2011; Baral et al., 2007; Joshi et al., 2006). Furthermore, WHO also uses the World Bank income groups as one of the classification methods for their health statistics and information systems (World Health Organization, 2017). Any review that considers studies on all countries was still included if there is a clear distinction between findings from LMICs and high-income countries (HIC).

#### 4.2.3 **Types of interventions**

For the purpose of this review, I defined health insurance as any programme that attempts to pool the financial risk of seeking health care by collecting contributions from a group of people (Folland, Goodman and Stano, 2014). Depending on the financing sources and who manages the risk pools, health insurance can be classified into private and public. Public insurance is generally financed through either taxation systems or payroll contributions to a social security scheme, while private insurance is financed through private health premiums (Gottret and Schieber, 2006). This overview focuses on public health insurance only. Pauly et al. (2006) provides a good overview of the role of private insurance in developing countries. Reviews that

included both public and private health insurance were also included if there is a clear distinction between those two types in their analyses.

Health insurance is not the only means to increase the demand for health services. Reviews studying other types of financial incentives, such as voucher schemes or cash transfers, were excluded (Pega et al., 2015; Grainger et al., 2014; Lagarde, Haines and Palmer, 2007). The financing structure of health insurance programmes may differ in revenue collection methods and provider payment schemes, both between and within countries. For example, local governments in a highly-decentralised country are given greater level of discretion in determining the reimbursement rate for any usage of health services. This review did not place any restrictions on the health financing structure of the health insurance programme.

#### 4.2.4 **Types of outcomes measures**

Three main outcomes of interest were included – access to healthcare, financial protection, and health outcomes.

- Access to care is commonly measured by changes in utilisation patterns of health services (e.g. immunisation coverage, number of doctor visits, and rates of hospitalisation).
- Financial protection is commonly measured by changes in out-of-pocket expenditures (OOP) at either household or individual level. I also considered specific measures reflecting a more comprehensive picture of financial protection, including catastrophic health expenditure or impoverishment from medical expenses.
- Changes in health outcomes measured by any quantities, such as nutritional status, morbidity and mortality rates.

The scope of this overview is not restricted to any particular level of healthcare delivery. All types of health services were included in this review, including maternal health care, chronic diseases, and preventive care.

#### 4.2.5 Information sources

A wide-ranging search for relevant articles was conducted on 7 March 2016 using several scientific journal databases, including the Centre for Reviews and Disseminations (CRD) and Cochrane Database for Systematic Reviews, Medline, Embase, Econlit, CINAHL Plus via EBSCO, and Web of Science. The following medical subject heading (MESH) terms were used for Cochrane Reviews “Developing Countries” (AND) “Insurance, Health”. More detailed keywords were used in other databases, especially in databases that are not specific to systematic reviews. To limit the search to include review papers only, the filter “review\$.ti.ab” was used for Medline and similar keywords were also used in other databases. Inquiries were also made to experts in global health, and WHO and World Bank databases were used to identify grey literature. The full search strategy is outlined in Table A-1 (see Appendices). There were no language or publication date restrictions. Translation from other language to English was performed, if necessary, employing an official translator.

#### 4.2.6 Data collection process

Two independent reviewers screened all titles and abstracts of the initially identified reviews to determine if they met the inclusion criteria. Any disagreement was resolved through consensus. Full text articles were retrieved for the selected titles. Both reviewers used a standardised data collection form to extract the relevant information from the selected studies, including information on study period, language restriction, inclusion and criteria, assessment of quality, characteristics of the intervention under consideration and main findings. Two reviewers graded the overall findings of each review according to the following categories: “positive effect,” “negative effect,” “no effect,” or “not assessed.”



#### 4.2.7 Assessment of review quality

In order to determine whether the identified reviews were adequate to answer the research question while minimising any bias, the quality of the identified reviews was assessed using the Assessment of Multiple Systematic Reviews (AMSTAR) criteria, a widely-used measurement tool to assess the methodological quality of systematic reviews (Shea et al., 2009). It consists of 11 specific questions and each question is given a score of one if the specific condition is met and zero otherwise. Meanwhile, there is another version of measurement tool called Revised AMSTAR (R-AMSTAR). However, some reviewers had compared it with the original AMSTAR tool and recommended using the original AMSTAR because it is easier to apply with a comparable validity (Pieper et al., 2015; Kang et al., 2012). Furthermore, a study compared the interrater reliability of both tools using a weighted Cohen's Kappa statistic and found that R-AMSTAR is more difficult to apply consistently across sixty systematic reviews (Popovich et al., 2012). Therefore, AMSTAR tool is more preferred than R-AMSTAR.

One caveat of AMSTAR is it assumes that a good reporting of the methodology used translates to good methodological quality (Faggion, 2015). To complement AMSTAR, I also used the ROBIS tool, a newly developed tool to assess the risk of bias in systematic reviews (Whiting et al., 2016). The ROBIS tool covers four domains through which bias may be introduced into a systematic review: study eligibility criteria, identification and selection of studies, data collection and study appraisal, and synthesis and findings. The overall judgement on risk of bias can be classified into three categories: "Low," "High," and "Unclear." While both AMSTAR and ROBIS provide the overall quality of a systematic review, ROBIS enables the reviewer to examine more closely the potential of bias in a systematic review. ROBIS tool is therefore more explicit in detecting bias, but AMSTAR is more widely used in literature. In this review, I decided to apply both criteria to get the benefit from each tool.

## Section 4.3 Findings

In this section, I start by describing the process of study selection. I then present the results of the systematic search and a summary of characteristics across studies. I will briefly explain the quality assessment of the review and the primary studies within the review followed by findings of the overview.

### 4.3.1 Results of the search

Figure 4-1 portrays the flow chart of the review process. After a thorough systematic search, 1,436 studies were identified from electronic databases. Two more studies were found from the grey literature and via expert consultation. From a total of 1,438 studies identified, 27 systematic reviews were selected upon scrutiny of the title and abstract against the above-stated inclusion criteria. After screening the full-text versions of these selected reviews, a total of ten reviews were included for further narrative synthesis (Habib et al., 2016; Acharya et al., 2013; Comfort et al., 2013; Giedion et al., 2013; Robyn et al., 2013; Bucagu et al., 2012; Liang et al., 2012; Spaan et al., 2012a; Yu et al., 2008; Ekman, 2004). The full description of both included and excluded studies is included in the appendix (Table A-2). Table 4-2 and Table 4-3 summarise the findings and strength of evidence for each review based on AMSTAR and the ROBIS tool, respectively.

The quality of the ten selected reviews was mixed. Apart from Bucagu et al. (2012), who limited their search strategy to only one database supplemented by searching official documents from the government, all other reviews conducted comprehensive literature searches, including grey literature, and involved at least two reviewers in checking the selection and data extraction. Two out of the ten reviews – Acharya et al. (2013) and Giedion et al. (2013) – published *ex ante* protocols and provided the complete list of included and excluded studies.

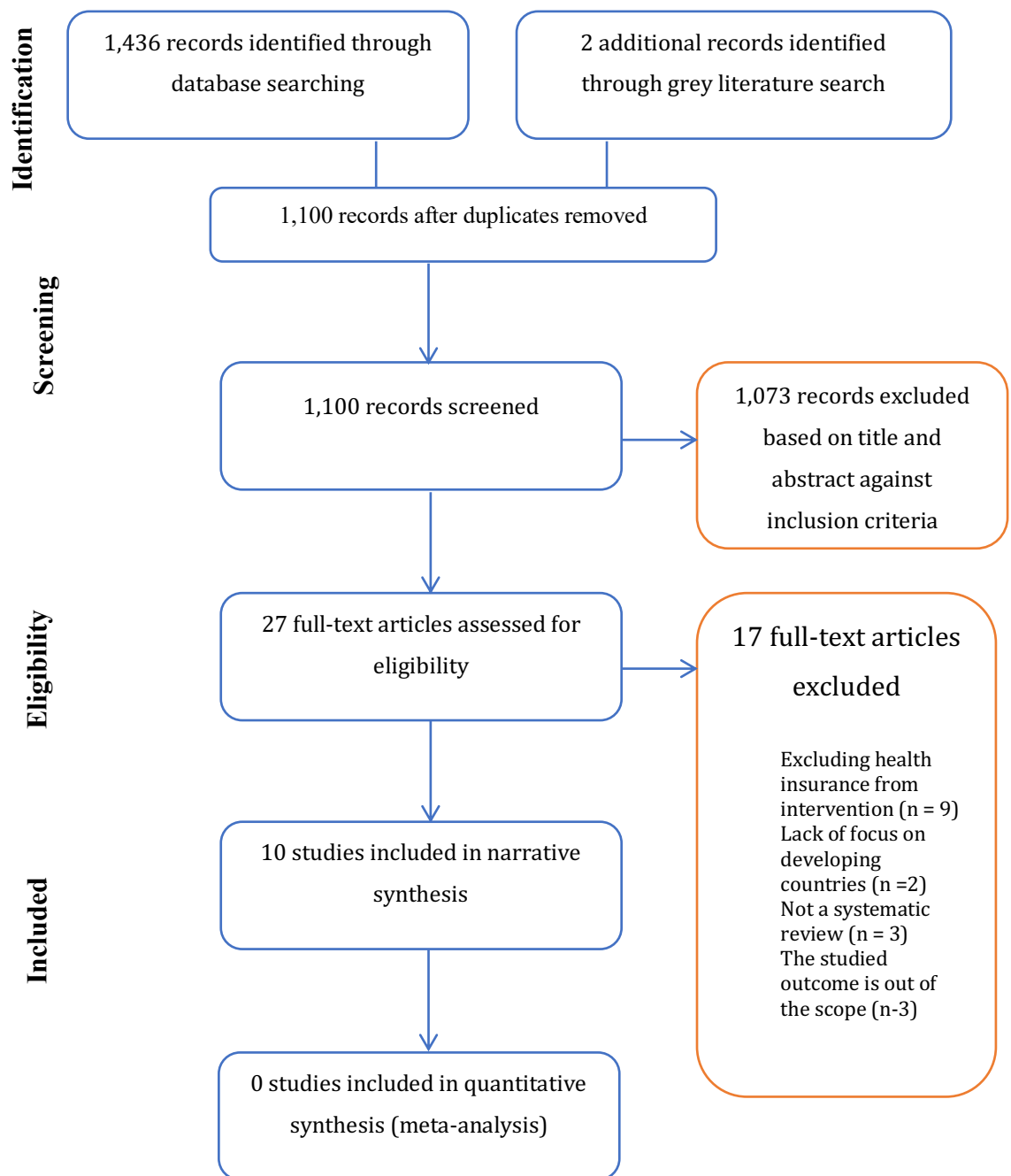


Figure 4-1 Flow chart for included and excluded systematic reviews following recommendation of PRISMA (Moher et al., 2009)

Table 4-1 Characteristics of included full-text reviews (N = 10)

Review	AMSTAR Score*	ROBIS score**	Literature Search and Eligibility Criteria	Population	Intervention	Outcome
Acharya et al. (2013)	9	Low risk	Search Strategy: Comprehensive searches including grey literature Year: 1980 - 2010 Language: No language restriction	Low-middle income countries (LMIC)	Health insurance	Utilisation of health care, healthcare expenditure, or health status
Giedion et al. (2013)	7	Low risk	Search strategy: Comprehensive searches including grey literature Year: 2000-2011 Language: Only English	LMIC	Any intervention under universal health coverage scheme	Access to health care, financial protection and health status
Ekman (2004)	6	Low risk	Search strategy: Comprehensive searches including grey literature. Year: Search from 1980-2002 Language: English, French, Portuguese, and Spanish	Low income countries	Community-based health insurance	Resource mobilisation, quality of care, provider efficiency, moral hazard, financial protection, OOP spending, and access to care
Liang et al. (2012)	6	Low risk	Search strategy: Comprehensive searchers including grey literature. Year: 2003-2010 Language: English and Chinese	China	Health insurance reform	Health outcome and financial protection
Habib et al. (2016)	6	High Risk	Search strategy: Pubmed, Google Scholar, Science Direct, and grey literatures. Year: 1995-2015. Language: English	LMIC	Micro health insurance	Financial protection

Spaan et al. (2012)	6	High risk	Search strategy: Comprehensive searches including grey literature Year: 1980-2011. Language: English, French, Spanish, or Portuguese	LMIC in Asia and Africa	Health Insurance	Resource mobilisation, service utilisation, quality of care, financial protection, social inclusion or community empowerment
Robyn et al. (2013)	5	Low risk	Search strategy: Comprehensive searches including grey literature Year: up to January 2010 Language: no language restriction	Low-middle income countries	Provider payment system in community-based health insurance	Provider participation, satisfaction, and retention; patient demand; quantity and quality of services provider; CBHI coverage and financial performance
Comfort et al. (2013)	5	High risk	Search strategy: key databases and consultation with panel of experts Year: 1980-2011 Language: English only	Low and middle income countries	Health Insurance	Maternal health indicators including demand, such as utilisation and supply, such as quality of care
Yu et al. (2008)	3	High risk	Search strategy: Comprehensive searches including grey literature Year: 1991-2008 Language: English and Chinese	Low-middle income countries	Health Insurance	Financial protection
Bucagu et al. (2012)	2	High risk	Search strategy: Pubmed and government documentation. Excluding other grey literatures. Year: 2005-2011 Language: English only	Rwanda	Performance-based financing and CBHI	Utilisation of maternal health services

\*AMSTAR = A measurement tool to assess systematic reviews. It consists of 11 questions with a point given for each mark. Higher marks reflect higher quality.

\*\*ROBIS score = Risk of Bias. It divides reviews into three categories: low risk of bias, high risk of bias, and unclear risk of bias

Table 4-2 Methodological quality of the included reviews based on AMSTAR criteria (N=10)

AMSTAR criteria *	Acharya (2013)	Giedion (2013)	Spaan (2012)	Ekman (2004)	Liang (2012)	Habib (2016)	Comfort (2013)	Robyn (2013)	Yu (2008)	Bucagu (2012)	% meeting criteria
<b>A priori protocol</b>	1	1	0	0	0	0	0	0	0	0	20%
<b>Data extraction</b>	1	0	1	0	1	1	0	0	1	1	60%
<b>Comprehensive search</b>	1	1	1	1	1	1	1	1	1	0	90%
<b>Grey literature</b>	1	1	0	1	1	1	1	1	1	0	80%
<b>List of studies</b>	1	1	1	1	0	1	0	0	0	0	50%
<b>Characteristics of included studies</b>	1	1	1	1	1	1	1	1	0	1	90%
<b>Quality assessment of studies</b>	1	1	1	1	1	1	1	1	0	0	80%
<b>Inclusion of study quality in formulating conclusions</b>	1	1	1	1	1	0	1	1	0	0	70%
<b>Method to combine the findings</b>	0	0	0	0	0	0	0	0	0	0	0%
<b>Assessing publication bias</b>	0	0	0	0	0	0	0	0	0	0	0%
<b>Conflict of interest</b>	1	0	0	0	0	0	0	0	0	0	10%
<b>Total score</b>	9	7	6	6	6	6	5	5	3	2	
<b>Column Percentage</b>	81%	64%	54%	54%	54%	54%	45%	45%	27%	18%	

\*Number 1 – 11 represents each of individual questions from AMSTAR criteria

Table 4-3 Methodological quality of the included reviews based on ROBIS tools (N=10)

ROBIS criteria *	Giedion (2013)	Spaan (2012)	Comfort (2013)	Bucagu (2012)	Ekman (2004)	Acharya (2013)	Liang (2012)	Yu (2008)	Robyn (2013)	Habib (2016)
<b>Study Eligibility Criteria</b>	Low	High	High	High	Low	Low	Low	High	Low	High
<b>Identification and selection of Studies</b>	High	High	High	High	Low	Low	Low	High	Low	High
<b>Data collection and study appraisal</b>	Low	Low	High	High	High	Low	Low	High	High	High
<b>Synthesis and findings</b>	Low	High	High	High	High	Low	Low	High	Low	High
<b>Overall risk of Bias</b>	Low	High	High	High	Low	Low	Low	High	Low	High

Most reviews provided the characteristics of the included studies, but only less than half reported those of excluded studies. No studies conducted a meta-analysis, which is not surprising considering the wide heterogeneity of health insurance schemes in different countries and even among different schemes within a country. Only Acharya et al. (2012) reported funding information for the primary studies and this review scored highest overall among the selected reviews.

Different studies had different strategies in their search protocol, and some noted that their protocol has been standardised in a separate paper. For example, Acharya et al. (2013) applied a standardised extraction form for screening the studies and grouped the primary paper based on the paper's ability to address selection bias or identification criteria. Meanwhile, Spaan et al. (2012) evaluated the extracted studies with a specified protocol that assess rigour, bias, validity and generalisability of the studies.

While most of the included reviews attempted to assess the quality of primary studies with variation in their methodology, the two lowest-scoring reviews, Bucagu et al. (2012) and Yu et al. (2008), did not explicitly assess this important aspect in their review and therefore did not consider the quality of the studies in their discussion. Meanwhile, Habib et al. (2016) assessed the studies using a checklist, but it did not evaluate clearly the selection bias problem. In their finding, they claimed to have convincing argument about the favourable effect of micro health insurance on financial protection despite this limitation.

#### **4.3.2 Criteria for quality assessment of primary studies**

In the process of conducting a systematic review, it is necessary to assess critically the quality of individual studies to ensure whether the study was affected by other endogenous factors, or bias, that might mislead our interpretation of its results (Petticrew and Roberts, 2006, pp.1–5). There are several approaches for assessing the quality of evidence, such as Grading of Recommendations, Assessment, Development and Evaluations (GRADE), which has been used extensively by

Cochrane (Cochrane, 2008). This approach is more often applied to RCTs conducted in clinical settings instead of public health or policy interventions, of which evaluation of the latter often relies on observational studies or, occasionally, cluster RCTs. The complexity of public health interventions and inability to discriminate between different types of observational studies have been cited as two common challenges to applying GRADE in public health settings (Rehfuess and Akl, 2013). In the context of this review, most primary studies within the selected reviews are observational studies with varying degree of quality; only very few studies used randomisation in allocating the treatment (Thornton et al., 2010; King et al., 2009). Among all the reviews, only one review utilised the GRADE assessment tool (Robyn et al. 2013). More detailed information on the quality assessment used by each review is included in Table 4-4.

Reviewers have attempted to assess the quality of primary studies using a variety of different methods. Different conclusions could have been reached, in principle, had a different method been used. In presenting their results, reviewers often used a subgroup of the studies with the highest scores, which should have reduced the heterogeneity of their findings. In this review, I decided to not exclude any review based on AMSTAR and ROBIS score but instead compared the findings from low-scored reviews with high-scored reviews.

*Table 4-4 Quality assessment criteria used in the selected studies (N=10)*

Author	Quality Assessment	Effect Evaluation
Acharya et al. (2013)	Based on whether a study attempts to solve selection problems using standardised method defined by the review's author. Then, it is classified into one of three categories: strongly meeting criteria, partially meeting criteria, or not meeting criteria	Vote counting. Only papers categorised as "strongly meeting criteria" were included
Bucagu et al. (2012)	There is no quality assessment	Vote counting



Comfort et al. (2013)	It is not clearly explained, but sometimes they commented on the study method.	Vote counting. No clear criteria for best evidence though the reviewers favored papers using propensity score, difference-in-difference, or instrumental variable method.
Ekman et al. (2004)	Quality grading based on author's own protocol. Seven questions with total 25 points possible. Grading Scale: - Three stars: 22-25 points; - Two stars: 17-21 points; - One star: 0-16 points	Categorised the evidence based on the quality assessment: - Grade 1: Strong evidence (minimum two 3 stars studies); 2: Moderately strong (one 3 stars studies plus minimum two 2 stars studies); 3: Weak (minimum two 2 stars studies); 4: Little or no evidence
Giedion et al. (2013)	Quality grading based on qualification matrix which includes five criteria: Study design, Data, General methodological, Specific methodological, and Discussion; Maximum score: 100;  Studies are classified based on their overall quality scores into four quartiles: Lowest (9-49), lowest-middle (50-63), upper-middle (64-70), and upper (>70)	Vote counting, but only for the upper and upper-middle groups.
Habib et al. (2016)	Used a Mirza and Jenkins checklist that used ten factors: 1) Study objectives, 2) Sample size justification, 3) Sample representation, 4) Inclusion and exclusion criteria, 5) Reliability and validity of measures, 6) Response rate and dropout rate, 7) Data description, 8) Statistical significance, 9) Discussion of generalizability, 10) Null findings	Vote counting
Liang et al. (2012)	Based on quality assessment criteria for quasi-experiment study adapted from Loevinshohn (1990), Thomas et al. (2004), and Gersten et al. (2005)	Vote counting
Robyn et al. (2013)	The Grades of Assessment, Development and Evaluation (GRADE), but the author only mentioned it in the discussion section, not in their findings	Vote counting
Spaan et al. (2012)	Based on HOI study Review Protocol on Health Insurance; point-based scoring: 0-38 with low (0-14), medium (15-29), and high (>29)	The impact is categorised into three: A: positive; B: negative; C: inconclusive. Overall impact is judged by: Strongly (+): $A/(A+B+C) > 60\%$ Weakly (+): $A/(A+B+C) > 30\%$ Strongly (-): $B/(A+B+C) > 60\%$ Weakly (-): $B/(A+B+C) > 30\%$
Yu et al. (2008)	There is no quality assessment	Vote counting

Table 4-5 Summary of Overall Effect from Selected Reviews (N=10)

Author (Number of included studies)	Access to Care	Financial Protection*	Health Status
<b>Acharya et al. (2013)</b> (N = 24)	13 out of 17 studies reported overall positive impact	10 out of 17 studies reported overall positive impact on out-of-pocket health expenditure	3 out of 6 studies reported overall positive impact on health status
<b>Bucagu et al. (2012)</b> (N = 3)	3 out of 3 studies reported positive impact	2 out of 2 studies that assessed the impact of CBHI on out-of-pocket health expenditure reported positive impact	N/A
<b>Comfort et al. (2013)</b> (N = 7)	3 out of 4 reported positive impact on access to maternal health services; the other study showed positive impact on health services in general, but not on maternal health services	N/A	Inconclusive due to small number of studies and conflicting findings among studies
<b>Ekman et al. (2004)</b> (N = 17)	8 out of 8 studies reported overall positive impact (one study with three stars and 7 studies with two stars)	5 out of 7 studies reported overall positive impact on out-of-pocket expenditure (4 studies with three stars and 3 studies with two stars)	N/A

<b>Giedion et al. (2013)</b> (N = 41)	25 out of 29 studies reported positive impact	13 out of 16 studies reported overall positive impact on out-of-pocket expenditures; 6 out of 9 studies reported overall positive impact on catastrophic expenditures; 3 out of 3 studies reported positive impact on reducing impoverishment	9 out of 18 studies reported overall positive impact on health status
<b>Habib et al. (2016)</b> (N = 13)	N/A	10 out of 13 studies reported overall positive impact on reducing OOP expenditure; 5 out of 7 studies also reported positive impact on reducing catastrophic health expenditure	N/A
<b>Liang et al. (2012)</b> (N = 12)	N/A	2 out of 4 studies reported positive impact while one study reported negative impact.	5 out of 12 studies reported overall positive impact on health outcomes; 3 out of 12 studies reported negative impact.
<b>Robyn et al. (2013)</b> (N = 34)	One cluster RCT showed no significant effect	N/A	N/A
<b>Spaan et al. (2012)</b> (N = 39)	27 out of 28 studies reported overall positive impact	17 out of 24 studies reported overall positive impact on financial protection (not specified)	N/A
<b>Yu et al. (2008)</b> (N = 56)	N/A	42 out of 56 studies reported positive impact; 6 out of 56 studies reported negative impact; 5 out of 56 studies reported no effect; and 3 out of 56 studies reported uncertain effect	N/A

*\*Positive impact on financial protection means that the insurance scheme either reduce the out-of-pocket health expenditure, reduce the likelihood of experiencing catastrophic health expenditure or impoverishment due to health spending*

### 4.3.3 Access to health care

Access to health care services was the most common measure used in impact evaluation studies of health insurance. Many factors are suggested to influence people's access to healthcare services, which include the characteristic of the individual—either fixed or amenable—and of the system in terms of health care delivery or in the broader system, such as politics environment or education (Andersen, 1995; Penchansky and Thomas, 1981; Aday and Andersen, 1974). Despite this complexity in defining access to health care, empirical studies tend to focus on utilisation of health care as the external validation of the effect of those various characteristics on people's access to health care services. Except for Ekman (2004), all the reviews chose health care utilisation as a proxy to measure access. Utilisation can be categorised into two groups: utilisation of general medical services and utilisation of specific health care services, such as maternal health or diabetes management.

Table 4-5 shows the summary of findings from the ten reviews included in this study. From seven reviews that included access to care as the primary outcome, six of them reported overall positive effect of health insurance in increasing health care utilisation. Spaan et al. (2012) reported that 26 out of 28 high-quality studies reported a positive effect of health insurance on increasing the probability of utilising health care services or increases in the number of visits to a doctor or other health care personnel. Giedion et al. (2013) also reported overall a positive and statistically significant effect of health insurance on health care utilisation from 21 out of 29 studies. Ekman (2004), who evaluated the literature on community-based health insurance, reported moderately strong evidence of a positive correlation between insurance and access to health care. However, among 12 studies from which he based his conclusion, only one study scored highly in quality assessment, and even that study did not control for endogeneity, a statistical term referring to correlation between the independent variable(s) with one or more unobserved factors excluded from the model that may affect the outcome variable.

Despite overall positive results from other review papers, Acharya et al. (2013) reported more nuanced results of the impact of state-subsidised or social health insurance schemes on health care access. They argued that papers using stronger methodology in terms of mitigating endogeneity tended to have inconclusive results compared with papers that did not fully account for endogeneity. Of the 17 studies included evaluating access to care, 13 reported significant positive results on the utilisation of health care services. The reviewers also observed that impact of these health insurance schemes did not appear to be homogeneous among different income levels, with more economically vulnerable groups getting greater benefits than more affluent groups, indicating heterogeneity of the impact across different populations. Overall, most reviews concluded a positive correlation between insurance and access to health care measured in terms of utilisation of health care services.

#### **4.3.4 Financial protection**

The direct benefit of health insurance is to protect its enrollees from financial problems arising from an expensive medical bill that could potentially lead to catastrophic expenditure and pushed below the poverty line. A common way to measure the protection effect of insurance is to measure out-of-pocket (OOP) health expenditure. However, the decreasing trend of OOP health expenditure is not sufficient to provide a full picture of the financial condition of a household. A household can have lower OOP health expenditure, but could still be forced into bankruptcy as long as the post-payment income cannot sustain their essential needs. Thus, it is essential to examine the catastrophic effect of the health expenditure on the household budget. This is commonly measured by calculating the proportion of health expenditure exceeding some pre-defined threshold in relation to the household's pre-payment income (Wagstaff, 2008). However, it also has a fundamental limitation in which it does not convey a clear picture of how far the catastrophic expenditure pushes the household into poverty. A household may spend 40% of its income to seek medical treatment, but still have enough income to sustain basic needs. On the other hand, a household may only need to spend 10% of its income to be pushed into poverty. To overcome this limitation, another measure,

impoverishment expenditure, can be used. A household is defined as being impoverished if its pre-payment income lies above the poverty line and its non-medical expenditure lies below the poverty line (Wagstaff and van Doorslaer, 2003). Among the studies included in this review, this measure is the least common method despite its superiority over the other methods. Overall, measuring the decrease of OOP expenditure was the most common measure, followed by the catastrophic expenditure using different thresholds.

From Table 4-5, there are eight out of ten reviews explored the effect on financial protection. Compared to the effect on utilisation, the overall effect on financial protection is less homogenous due to more studies showing the negative effect of health insurance on financial protection. It should be noted that positive effect on financial protection refers to lower level of out-of-pocket health expenditure or reduced event of catastrophic health expenditure. Spaan et al. (2012) and Ekman (2004) concurred that there is strong evidence that people with health insurance had lower out-of-pocket expenditure or lower probability of having catastrophic health expenditure, even though some high-quality studies found that the effect is only marginal (Jowett, Contoyannis and Vinh, 2003; Jutting, 2001; Carrin, Graeve and Devillé, 1999). Moreover, Acharya et al. (2013) provided more mixed evidence: two papers reported that individuals with health insurance had higher out-of-pocket expenditure than those without health insurance. Wagstaff and Lindelow (2008) evaluated the impact of health insurance in China on financial protection using IV regression estimations with fixed effect. They found that overall health insurance raises OOP health expenditure and the risk of catastrophic expenditure instead of reducing them.

Giedion et al. (2013) asserted that overall impact on financial protection leads to positive correlation, but they admitted that some studies that comparably have a more robust method in terms of solving the selection bias suggest otherwise. They also included both papers described earlier that showed higher OOP expenditure among the insured (Wagstaff et al., 2009; Wagstaff and Lindelow, 2008). From a cluster randomised trial in Nicaragua, Thornton et al. (2010) reported a reduction in

the expenditures on laboratory tests, a common out-of-pocket expenditure among the enrollees, but there is no reduction in overall OOP expenditures. Higher utilisation may lead to higher OOP expenditure if insurance does not cover the whole cost of seeking medical treatment, including transportation cost, drug cost, and laboratory cost. On the other hand, King et al. (2009) investigated the effect of Mexican social health insurance using cluster randomised trial and found a reduction of the proportion of catastrophic health expenditures between 23 and 55% and reduction of OOP expenditures for inpatient and outpatient medical care. Using regression discontinuity approach in estimating the effect of health insurance for poor in Georgia, Bauhoff, Hotchkiss, and Smith (2010) also reported a reduction in both outpatient and inpatient OOP expenditures especially among the elderly.

In contrast to OOP expenditures, relatively few papers that have evaluated the effect of insurance on catastrophic expenditures. In measuring the impact of NCMS on providing financial protection in China, Liang et al. (2012) only uses catastrophic health expenditure as the outcome. They reported that two out of four studies (Yan, Fan and Shi, 2009; Sun, 2005) suggest NCMS reduced the incidence of catastrophic health expenditure, but the other two studies, which have higher quality scores, reported otherwise (Wagstaff et al., 2009; Chinese Ministry of Health, 2007).

In other reviews, most of the studies reported a decrease in the probability of having experience of catastrophic expenditure for the insured (Galarraga et al., 2010; Flórez et al., 2009; King et al., 2009; Wagstaff, 2007). However, there is some variation in terms of the threshold determining the event of having catastrophic expenditure which can range from 5% to 40%. Only one study reported an increase, which also correlates with the increase in OOP expenditures (Wagstaff and Lindelow, 2008).

The last measure, impoverishment expenditure, has been researched even less among studies exploring the impact on financial protection. There are only three papers within the review by Giedion et al. (2012) and all of them reported a decrease in impoverishment expenditure events among people who were insured (Flórez et

al., 2009; Yip and Hsiao, 2009; Wagstaff and Yu, 2007). Other reviews did not consider this measure in their findings.

#### 4.3.5 Health status

Health status is often considered to be the primary long-term outcome of health insurance, but very few studies attempted to measure it, and, unlike utilisation and financial protection, the choice of health outcome is not standardised. Below I reported findings from three reviews that included health status as the outcome measure.

Acharya et al. (2013) reported only three out of six high-quality primary studies that provided strong evidence of positive correlation between insurance and health status. For example, a study in Mexico evaluated reported better diabetic management among people who were insured by *Seguro Popular*, a health insurance for poor (Galarraga et al., 2010). In China, one study evaluated the impact of Rural Mutual Health Care (RMHC) a community-based health insurance in Western China and found that RMHC significantly reduced pain/discomfort and anxiety/depression as well as improved mobility and activities of daily living among the elderly (Wang et al., 2009).

Comfort et al. (2013) reported that among two studies that evaluated maternal health status, one study reported a decrease in the maternal mortality rate in the Sorsogon province of the Philippines, but the method used, trend analysis, was not adequate to account for selection bias (Huntington, Banzon and Recidoro, 2012). Another study that was considered to have a more rigorous method by controlling endogeneity with propensity score matching and difference-in-difference found no effect of the New Cooperative Medical Scheme (NCMS) on the mortality rate of young children and of pregnant women in China (Chen and Jin, 2012).



Liang et al. (2012) was the only review that reported studies showing a negative impact of health insurance on health outcomes (Shen and Jiang, 2008; Chinese Ministry of Health, 2007). However, those two studies were scored lower compared to other studies that reported positive or no impact. Even when the evidence is taken only from the high scoring group, the result was still inconclusive with five studies reported positive impact and three studies reported no impact of health insurance on health status.

## **Section 4.4 Discussion**

This review provides an overview of the empirical literature on the impact of health insurance, as identified by ten systematic reviews, synthesising the available evidence captured by published reviews. With regard to **access to care**, most of the reviews focused on utilisation of health care facilities, either for general medical care or for maternal health services. Overall, there is agreement that health insurance had a positive effect on utilisation of health care services, although some of the studies, particularly those which better address endogeneity problems, showed mixed results.

There are several possible reasons to explain the mixed findings. First, fees for treatment are only one of several barriers to accessing care. Penchansky and Thomas's (1981) definition of access to medical care lists five dimensions of access (availability, accessibility, accommodation, affordability, and acceptability). Insurance may ease the financial barriers associated with fees for treatment (i.e., affordability) but may not be adequate to facilitate other dimensions to access. For example, Thornton et al. (2010) found that the enrollees perceived lower quality services and discrimination from the providers contracted by the Ministry of Health, compared to providers contracted by the insurance programme for formal sector employees and other private health providers, which relates to acceptability of access in the Penchansky and Thomas model. Similarly, another study suggested that the inaccessibility of facilities still deterred beneficiaries from utilising health care

services even though they no longer had to pay (Wagstaff, 2010a). If these other aspects of access have not been fulfilled, improving affordability through insurance might provide little benefit toward expanding access to care.

Secondly, the target population for health insurance programmes, especially programmes aimed at improving coverage among the poor, may be not fully aware of the programme's benefits. This was found to be the case by Thornton et al. (2010) in Nicaragua and by Bauhoff, Hotchkiss and Smith (2011) in Georgia, where a medical insurance programme did not increase utilisation of health services among the poor. Third, the time between the introduction of the programme and its evaluation for many of the papers reviewed may not have been sufficient for the data to be meaningful, since care seeking behaviour and, consequently, utilisation responses can be expected to be lagged (Wagstaff, 2010a). Fourth, the null findings may reflect a substitution effect where people choose to seek treatment in modern facilities, that otherwise cannot be accessed without insurance, over traditional practices. Axelson et al. (2009), for example, reported a small impact on overall utilisation of health care, but they also found a significant substitution effect away from private to public providers and from primary to higher level of care. Lei and Lin (2009) found no increase in utilisation of formal medical services but instead found decrease in the use of traditional practices and increase the utilisation of preventive care.

Evidence on whether health insurance had a positive effect on **financial protection** was unclear. Some papers suggested that the effect may even be negative, with those covered by health insurance having increased risk of incurring high OOP expenditures (Wagstaff et al., 2009; Wagstaff and Lindelow, 2008; Ekman, 2007; Dong et al., 1999). Several reviewers have critiqued the use of conventional measures of financial protection, such as out-of-pocket or catastrophic expenditures and impoverishment, as inadequate in capturing the true financial consequences of having an illness or other health need on at the household level (Acharya et al., 2013; Giedion et al., 2013). This implies that the positive associations observed likely overestimate the effect of health insurance. Giedion et al. (2013) argued that when people seek medical treatment, they often face financial barriers other than medical

fees, such as transportation costs, which may explain why distance to the health facility may deter people from seeking necessary treatment in low- and middle-income countries. Another shortcoming of conventional measures of financial protection is the interpretation of low or zero OOP expenditures (Giedion et al. 2013). While the common assumption is that households with low or zero OOP expenditures have better financial protection, another possible interpretation is that these households may have been unable to afford other health-seeking related costs and forego the necessary medical treatment (Moreno-Serra, Millett and Smith, 2011).

Several studies have suggested replacing existing measures with a more comprehensive measure of financial protection. Either a “needs-adjusted” estimate based on utilisation patterns and medical expenditures (Moreno-Serra, Millett and Smith, 2011), or a multidimensional approach that uses information on total cost of illness, coping strategies, and household consumption patterns (Ruger, 2012) can provide a more comprehensive financial protection profile. Empirical studies of the application of both methods are still rare and future studies should prioritise investigating the usefulness of these approaches.

This overview also demonstrated mixed evidence on the effect of health insurance on **health status**. Reviews that included health status as one of their main outcomes offered several explanations of these findings, most of which referred to flaws in the evaluation plan for the insurance schemes (Acharya et al., 2013 and Giedion et al., 2013). First, the outcome measure may not have matched the goals of the scheme. Second, health status is considered a long-term impact, so more time is required for its effects to be revealed in the data. Third, and probably most importantly, is the dependence of health status on other short-term effects. Before the improvement of health status can begin to be revealed in the data, it requires a prior positive correlation between health insurance and short-term outcomes, such as utilisation of health care services.

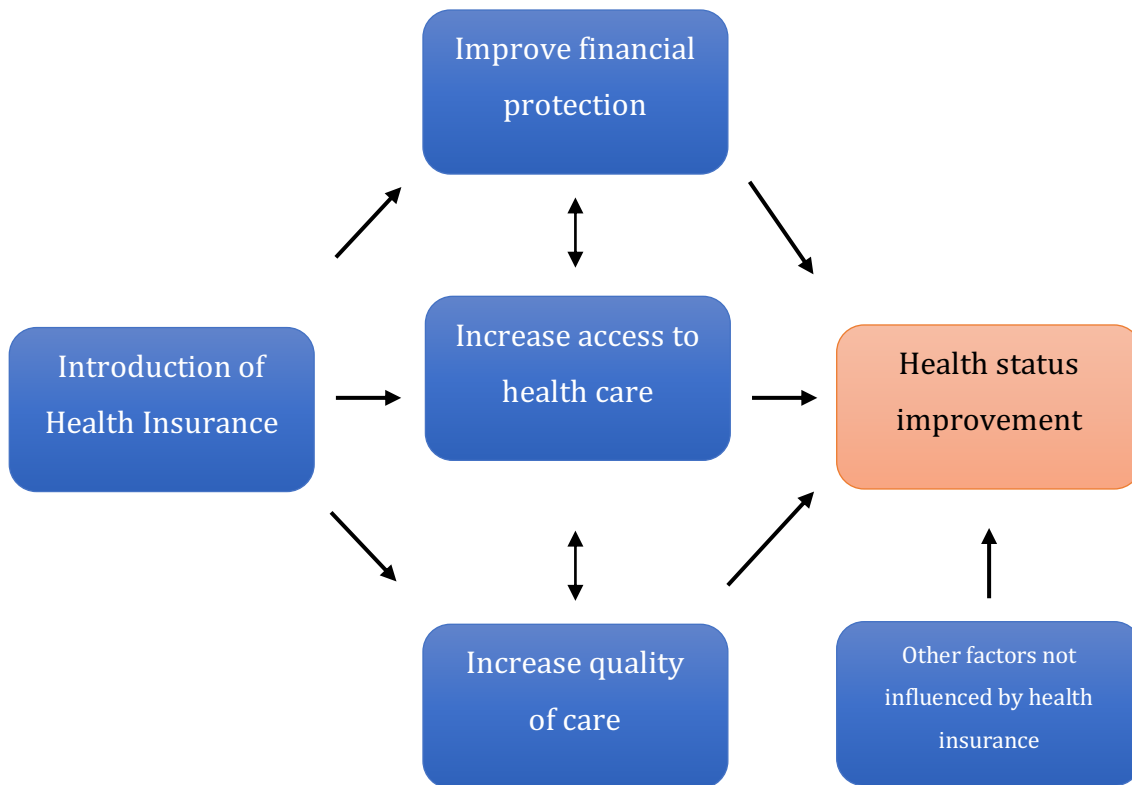


Figure 4-2 Pathway from health insurance leading to improvement of health status

*\*adapted from Comfort et al. (2013) with modification*

The pathway from the introduction of health insurance to health status improvement requires several conditions to be met before any apparent health effects can be detected (Figure 4-2). Reducing the financial barrier of treatment fees may increase access to health care and protect individuals and households from catastrophic health expenditure and impoverishment. In some cases, health insurance programmes may also increase the quality of care accompanied by investment to improve supply. In that case, increasing use of health care services may improve health status if quality of care is not reduced. The underlying pathway of health insurance to improve health status could be from better financial protection, not by only increased access to healthcare per se (Quimbo et al., 2011). Increases in OOP expenditure from other costs (e.g., co-payments, informal payments or transport costs) could reduce this benefit (Acharya et al., 2013). Finally, there are a number of external factors that affect health status, but are not influenced directly by the introduction of health insurance scheme. Another way to interpret the pathway is that when a health insurance scheme does not increase access to health care, improve

quality of care, or improve financial protection, it should not be surprising to see that the scheme has no effect on health status. Indeed, any improvement in health status should be interpreted with caution as it may result from external factors not necessarily affected by insurance. It is important to follow a pathway of how insurance would affect health status according to its benefits structure and payment mechanisms.

A final explanation for negative or inconclusive results in some of the studies evaluating the impact of the introduction of health insurance schemes on health status is that other alternatives for medical care might exist for individuals without health insurance. In outpatient settings, for example, public facilities often provide low-cost treatment for everyone. There may also be spillover effects from the existence of insurance to the non-insured in terms of increasing supply of health care, improving quality and quantity which is available to all, not just for the enrolees. Without proper consideration in their analysis, evaluators might draw a misleading conclusion that the programme has no effect where actually it might have a subtler effect but concealed with unexpected higher baseline in the control group.

Heterogeneity is always an issue for systematic reviews and can be exacerbated in an overview like this. I found heterogeneity in, first, benefits and payment structures, which differed widely among health insurance schemes. More generous benefits structures may induce more utilisation and provide better financial protection, while those that still utilise fee-for-service structure may provide less protection. For example, a review of community-based insurance (CBI) reported that provider payment can affect the patient demand for CBI services, as well as population enrolment, risk pooling, and financial sustainability of CBI (Robyn et al., 2013). In addition, the inclusion and exclusion criteria for each review in this overview were slightly different. Spaan et al. (2012), for example, included only evaluations of insurance programmes in Asia and Africa, while Ekman (2004) included only studies pertaining to CBI. Giedion et al. (2013) had a wider scope of interventions, including other means of demand-side intervention that promoted universal health coverage. The differences in primary studies included among the reviews was not however

wholly explained by inclusion criteria, but also by how thoroughly reviewers searched grey literature. Health insurance studies tend to be assessed by health authorities and there is less pressure to publish the results in peer-reviewed journals, especially if the study found no positive effects. Spaan et al. (2012) reported that even though CBHI are quite popular in Africa, few countries have published findings of impact evaluations in a peer-reviewed journal. The findings from grey literature are important to get a more comprehensive picture of the impact of health insurance on different health outcomes, but they also tend to be of lower quality than peer-reviewed publications, which could affect our confidence in the overall findings.

No reviews conducted a meta-analysis, which is unsurprising considering the wide heterogeneity of health insurance schemes in different countries and even among different schemes within a country. The included reviews were all narrative, supplemented by trend analysis and vote counting which does not permit any kind of point estimate. Despite wide disagreement in various outcome indicators of interest among these studies, out-of-pocket expenditure appeared to be quite standardised among the studies. It may be worth expanding the review by Essue et al. (2015), which has pioneered the synthesis of OOP expenditures in developed countries.

## **Section 4.5 Conclusion**

The findings from this overview suggest that there is good evidence that health insurance can improve access to health care, especially in increasing utilisation of health care services. It should be noted that some schemes were unable to produce any effect due to the inability of the scheme to reduce other barriers, such as acceptability (e.g., negative perception of the quality of public facilities), affordability (e.g., as result of other treatment-related costs that are not covered by the scheme), and accessibility (e.g., distance). In addition, some schemes appeared not to have been able to reach the target population, which suggests that low awareness of the programme might explain the observed null effects of insurance on utilisation.

Secondly, there is some evidence to suggest that publicly-funded health insurance can reduce out-of-pocket expenditure, but a smaller set of evidences using arguably more robust methods showed otherwise. It is possible that the increased demand from health insurance may increase health care expenditures, particularly if the insurance does not cover the entire cost of care, although it is important to note that much of the evidence for increased health expenditure came from China, where providers are reimbursed in proportion to the actual cost. Such reimbursement structures might lead to the manipulation of pre-reimbursed cost to maximise the post-reimbursed payment, and it is unclear whether or not this increased cost is associated with improved health status.

While ultimately improved health status is the long-term goal of health insurance programmes, only comparatively few studies were conducted to evaluate this outcome. The evaluator needs take care when choosing the appropriate health status variable, to ensure that the selection is driven by the framework on how insurance affects health outcomes, and this process may depend on many technical aspects of the scheme, including coverage benefits and the provider payment structure.

Considering the large amount of research in this field and rapid new studies on health insurance given more countries were attempting to introduce health insurance in national level, I decided to update one of the most rigorous review identified in this chapter with additional methodological approach in assessing the quality of the primary studies. This updated review will be presented in the next chapter (Chapter 5). There is also a need to summarise the available evaluation methods of measuring the impact of health insurance. This summary will allow future studies to learn the best practice which may improve our knowledge about the impact of health insurance programme, especially in LMICs. This method review (Chapter 6) will be discussed after the updated review chapter.





# **Chapter 5 Updated systematic review of the impact of health insurance**

## **Section 5.1 Introduction**

From the previous chapter, I have identified ten systematic reviews with Acharya et al. (2013) being the most comprehensive one. The majority of existing reviews have suggested that publicly-funded health insurance has typically shown a positive impact on access to care, while the picture for financial protection was mixed, and the evidence on the impact on health status was barely existing. This chapter offers a systematic review of the recent fast growing evidence on the impact of health insurance on health care utilisation, financial protection and health status in LMIC. I chose to update the search strategy of Acharya's review because it has the highest quality grading in terms of review quality based on AMSTAR and ROBIS. Since the publication of Acharya et al. (which conducted literature searches in July 2010), the empirical evidence on the impact of health insurance has significantly expanded in terms of quantity and also in terms of quality, with growing use of sophisticated techniques to account for statistical challenges (i.e. insurance selection bias) (Cameron, Mishra and Brown, 2016). Thus, this study makes an important contribution towards our understanding of the impact of health insurance in LMICs, taking particular care in quality appraising the studies. Furthermore, I explore evidence of moral hazard in insurance membership, an aspect that was not addressed in the Acharya's review (Acharya et al., 2013)

## **Section 5.2 Methods**

This review was planned, conducted, and reported in adherence with PRISMA standards of quality for reporting systematic reviews (Moher et al., 2009)

### 5.2.1 Participants

Only studies focusing on LMIC are included, as measured by per capita gross national income (GNI) estimated using the World Bank Atlas method per July 2016 (World Bank, 2016).

### 5.2.2 Intervention

This review focuses on publicly-organised health insurance only. Primary studies that included both public and private health insurance were also considered, if a clear distinction between the two was made in describing their finding. Studies examining other types of financial incentives to increase the demand for healthcare services, such as voucher schemes or cash transfers, were excluded.

### 5.2.3 Control group

An uninsured group with no form of insurance had to be used as the control group. Multiple comparison groups were allowed, but an uninsured group had to be included.

### 5.2.4 Outcome measures

I focus on three main outcomes:

- Access to care which is commonly measured by utilisation of health care services (e.g. immunisation coverage, number of visits, rates of hospitalisation).
- Financial protection, as measured by changes in out-of-pocket (OOP) health expenditure at household or individual level, and also catastrophic health expenditure or impoverishment from medical expenses.
- Health status, as measured by morbidity and mortality rates, indicators of risk factors (e.g. nutritional status), and self-reported health status.

The scope of this review is not restricted to any level of healthcare delivery (i.e. primary or secondary care). All types of health services were considered in this review.

### **5.2.5 Types of studies**

This review included randomised controlled trials, quasi-experimental studies (or “natural experiments” (Craig et al., 2012)), and observational studies that account for selection bias due to insurance endogeneity (i.e. bias caused by insurance decisions that are correlated with the measured outcomes). Observational studies that did not take account of selection bias were excluded.

### **5.2.6 Databases and search terms**

The systematic search for relevant articles was conducted on 6 September 2016 using peer-reviewed databases (Medline, Embase, Econlit, CINAHL Plus via EBSCO and Web of Science) and grey literatures (WHO, World Bank, and PAHO). The search was restricted to studies published since July 2010, i.e. just after the period covered by the earlier Acharya et al. (2013) review. No language restriction was applied. Full details of the search strategy are available in Table A-2 (see Appendices).

### **5.2.7 Screening and data extraction**

Two independent reviewers screened all titles and abstracts of the initially identified studies to determine whether they satisfied the inclusion criteria. Any disagreement was resolved through mutual consensus. Full texts were retrieved for the studies that met the inclusion criteria. A data collection form was used to extract the relevant information from the included studies.

### **5.2.8 Assessment of study quality**

To assess the quality of the identified studies, I used the Grades of Assessment, Development and Evaluation (GRADE) system checklist (Guyatt et al., 2008; Cochrane, 2008) which is commonly used for quality assessment in systematic reviews. However, GRADE does not differentiate observational studies based on its

ability to control for selection bias. Thus, I supplemented the GRADE score with another checklist, the 'Quality of Effectiveness Estimates from Non-randomised Studies' (QuEENS) (Faria et al., 2015)

A fundamental requirement for evaluating methods to estimate the treatment effect in non-randomised studies is to have a clear understanding of the process of treatment assignment. This will be case specific and therefore it is expected that any study using non-randomised data will require a detailed discussion about the nature of the data, how it has been collected/generated and the mechanism of treatment assignment. QuEENS checklist classifies studies into three categories: low, medium and high risk of bias, based on the strength of study's arguments to support several critical assumptions needed to justify the appropriateness of the models and to substantiate the results. Some important notes regarding the grading of studies:

- Randomised studies were considered to have low risk of bias.
- Non-randomised studies that account for selection on observables variables, such as propensity score matching (PSM), were categorised as high risk of bias unless they provided adequate assumption checks or compared the results to those from other methods in which case they may be classed as medium risk.
- Non-randomised studies that account for selection on both observables and unobservables, such as regression with difference-in-differences (DiD) or Heckman sample selection models, were considered to have medium risk of bias. Some of these studies could be downgraded or upgraded depending on sufficiency of assumption checks and comparison with results from other methods.

Finally, heterogeneity of health insurance programmes across countries and variability in empirical methods used across studies precluded a formal meta-analysis. I therefore conducted a narrative synthesis of the literature and did not report the effect size. Throughout this review, I only considered three possible effects: positive outcome, negative outcome, or no statistically significant effect (here defined as  $p\text{-value} > 0.1$ ).

## Section 5.3 Results

### 5.3.1 Results of the search

My database search identified 8,755 studies. Five additional studies were retrieved from grey literature. After screening of titles and abstracts, 118 studies were identified as potentially relevant. After reviewing the full-texts, 68 studies were included in the systematic review (see Figure 1 for the PRISMA diagram). A full description of included studies is presented in the appendix (Table A-3).

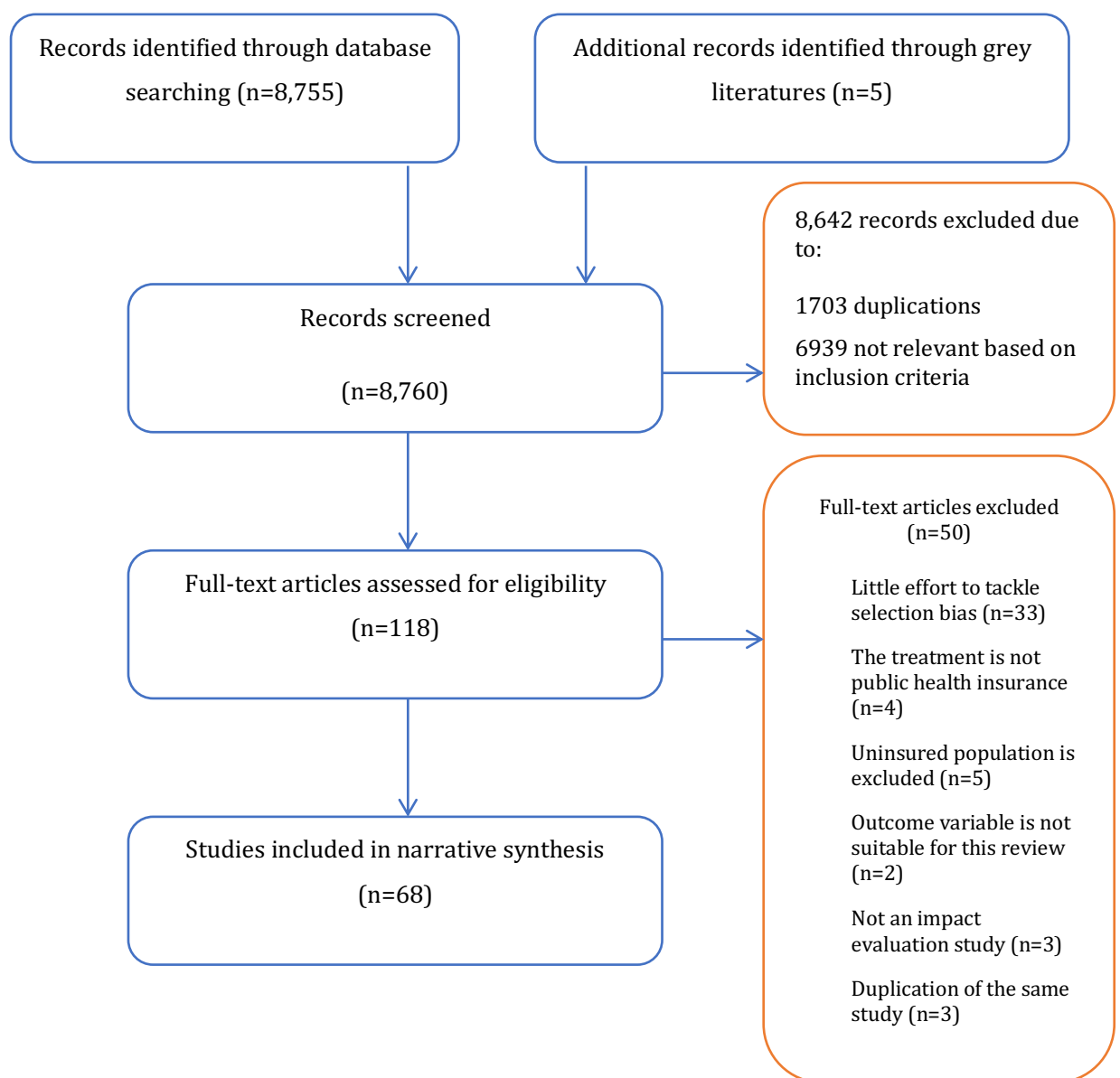


Figure 5-1 PRISMA flow diagram for included and excluded studies

### 5.3.2 Quality assessment of the included studies

While Acharya et al. (2012) divided the included studies according to the type of insurance and whether they met the identification criteria or not, I separated the studies by two different quality assessment criteria: QuEENS and GRADE. Normally, GRADE classifies a study into four criteria: high, moderate, low, and very low, in which the 'high' is considered superior to 'low'. However, there is no study categorised as 'high' in this review even though three randomised studies have been identified. Those three studies failed to reach the 'high' category because of their lack of allocation concealment and blinding, which are almost impossible for any public health intervention in general. In addition, GRADE has a rule to classify any observational study in the 'low' group which could be upgraded if the treatment effect is very large, if the bias is likely to underestimate the treatment effect, or the presence of the dose response. However, none of the non-randomised studies are eligible for this upgrade. Furthermore, 11 studies were downgraded due to either their failure to solve the selection bias issue or the lack of detail in their estimation methods.

The second criteria, QuEENS, is also further divided into three categories based on their potential risk of bias: Low, Moderate, and High. The QuEENS criteria places more emphasis on the sound arguments to support some critical assumptions needed to justify the appropriateness of the models and to substantiate the results. Therefore, it requires a detailed discussion on the methodology aspect of the studies. In this review, most studies in the 'high risk' category do not report adequate discussion of their estimation model in their method section. Meanwhile, studies in the low risk category are appraised for their detail, transparent discussion and convincing argument underpinning their choice of estimation methodology.

Compared to GRADE, more studies are classified as a high quality based on QuEENS; 10 out of 52 studies are judged as having low risk of bias based on QuEENS and only 4 out of 52 studies are classified as moderate quality based on GRADE. Meanwhile, there are 22 studies qualified as a high risk of bias out of 52 included studies which

implies that QuEENS could be more effective to separate between good and bad quality studies, considering the ability of the studies to overcome both observable and unobservable bias.

### 5.3.3 Access to care

Figure 5-2 and Table 5-1 collate the evidence on the effects of health insurance on access to healthcare services. Despite the complexity of defining access to care, many studies have chosen to proxy access by measuring the utilisation of health care services. Out of 40 studies, 32 studies reported positive effect of increased utilisation of care, with a mixed quality of evidence. Among the higher quality studies, i.e. those that suitably controlled for selection bias reflected by moderate or low GRADE score and low risk of bias (score = 3) on QuEENS, seven studies reported a positive relationship between insurance and utilisation, one study (Raza et al., 2016) reported statistically non-significant effect, and another study found a negative effect (Sheth, 2014).

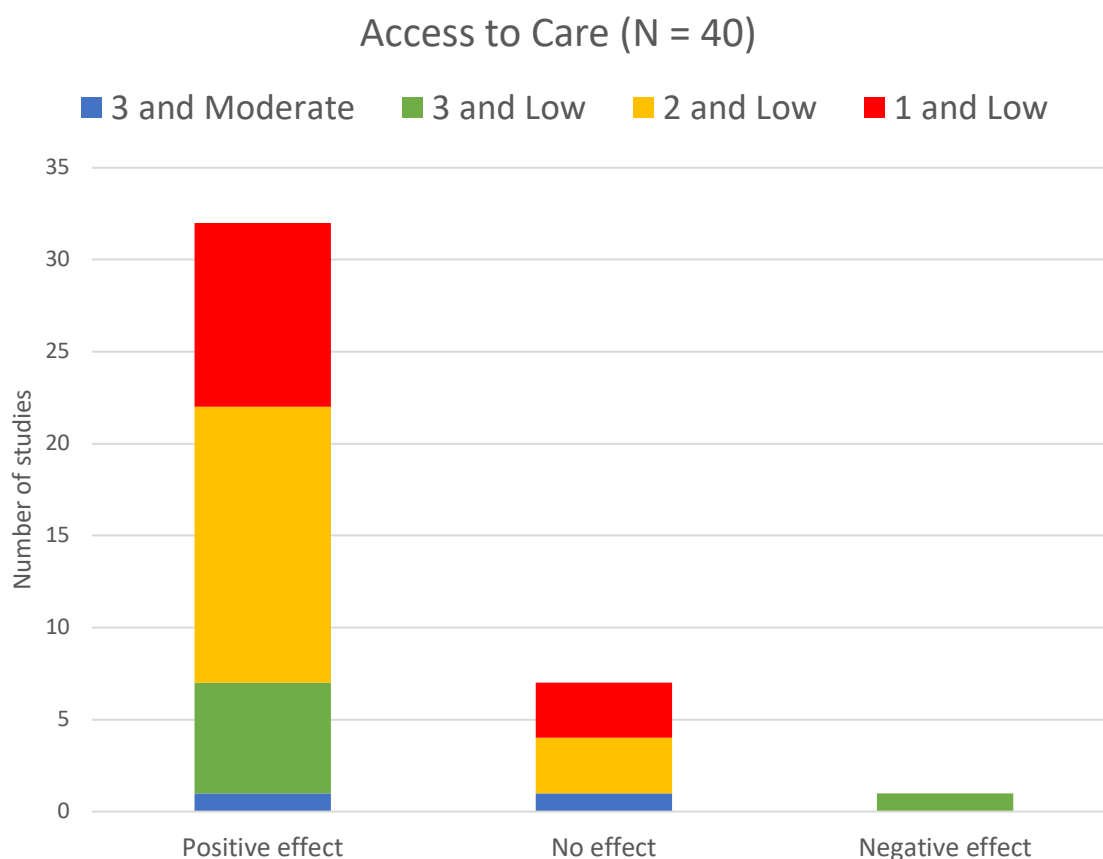


Figure 5-2 Summary of the impact of health insurance on access to care

\* Queens score: 1 = high risk of bias; 2 = moderate risk; 3 = low risk

† Grade score: Low = low quality; Moderate = moderate quality

The evidence on utilisation can also be grouped based on type of care: curative or preventive care. The evidence on the utilisation of curative care mostly suggested a positive effect, with 30 out of 38 studies reporting a positive and statistically significant effect. However, the evidence on preventive care is less clear with 4 out of 7 studies reporting a positive effect, two studies found a negative effect and one study reported no effect.

Next, I will present the findings grouped based on country location of the studies to minimise the heterogeneity in the structure of health insurance scheme.

Table 5-1 Summary of studies reporting utilisation of health care (N=40), by countries and year

Study	Country	Insurance*	Effect	QUEENS**	GRADE†
(Robyn and et al., 2012)	Burkina Faso	CBHI	0	3	Moderate
(Robyn et al., 2012)	Burkina Faso	CBHI	+	1	Low
(Levine, Polimeni and Ramage, 2016)	Cambodia	CBHI	+	3	Moderate
(Babiarz et al., 2010)	China	SHI	0	2	Low
(Lu, Liu and Shen, 2012)	China	SHI	+	2	Low
(Chen, Liu and Xu, 2014)	China	SHI	+	2	Low
(Hou et al., 2014)	China	SHI	+	2	Low
(Liu and Zhao, 2014)	China	SHI	+	2	Low
(Cheng et al., 2015)	China	SHI	+	2	Low
(Liao, Gilmour and Shibuya, 2016)	China	SHI	+	1	Low
(Trujillo et al., 2010)	Colombia	SHI	+	2	Low
(Hassan, Jimenez and Montoya, 2013)	Colombia	SHI	+	1	Low
(Miller, Pinto and Vera-Hernandez, 2013)	Colombia	SHI	+	3	Low
(Hou and Chao, 2011)	Georgia	SHI	+	3	Low
(Zoidze et al., 2013)	Georgia	SHI	0	1	Low
(Gotsadze et al., 2015)	Georgia	SHI	0	1	Low
(Blanchet, Fink and Osei-Akoto, 2012)	Ghana	SHI	+	1	Low
(Yilma, Van Kempen and De Hoop, 2012)	Ghana	SHI	+	3	Low
(Abrokwah, Moser and Norton, 2014)	Ghana	SHI	+	1	Low
(Brugiavini and Pace, 2015)	Ghana	SHI	+	2	Low
(Fenny et al., 2015)	Ghana	SHI	+	1	Low
(Sheth, 2014)	India	CBHI	-	3	Low
(Sood et al., 2014)	India	SHI	0	2	Low
(Raza et al., 2016)	India	CBHI	0	3	Moderate
(Sparrow et al. 2013)	Indonesia	SHI	+	2	Low
(Alkenbrack and Lindelow, 2015)	Lao PDR	CBHI	+	2	Low
(Rivera-Hernandez et al., 2016)	Mexico	SHI	0	2	Low
(Bernal, Carpio and Klein, 2014)	Peru	SHI	+	3	Low



(Dhillon et al., 2012)	Rwanda	CBHI	+	1	Low
(Lu et al., 2012)	Rwanda	CBHI	+	2	Low
(Panpiemras et al., 2011)	Thailand	SHI	+	1	Low
(Ghislandi, Manachotphong and Perego, 2015)	Thailand	SHI	+	2	Low
(Limwattananon et al., 2015)	Thailand	SHI	+	2	Low
(Makhloufi, Ventelou and Abu-Zaine, 2015)	Tunisia	SHI	+	1	Low
(Nguyen, 2012)	Vietnam	SHI	+	3	Low
(Nguyen and Wang, 2013)	Vietnam	SHI	+	2	Low
(Guindon, 2014)	Vietnam	SHI	+	2	Low
(Nguyen, 2014)	Vietnam	SHI	+	1	Low
(Palmer et al., 2015)	Vietnam	SHI	+	3	Low
(Nguyen, 2016)	Vietnam	SHI	+	2	Low

\* SHI = Social Health Insurance; CBHI = Community-based Health Insurance; \*\* Queens score: 1 = high risk of bias; 2 = moderate risk; 3 = low risk; † Grade score: Low = low quality; Moderate = moderate quality; High = high quality

China has been the subject of a long health reform since 2003 and many studies have been published to evaluate the success of this health reform. Currently there are four big health insurance schemes covering different target population: NCMS (for rural residents), GMI (for the government's employees), UEBMI (for formal workers in urban area), and URBMI (for informal workers in urban area). For insurance under the New Cooperative Medical System (NCMS), Lu, Liu, and Shen (2012) reported a positive effect on probability of seeking medical care and an increased the number of outpatient visits. Hou, et al. (2009) constructed the NCMS generosity index based on the reimbursement rates from different insurers under NCMS contract. They found that a 40% change in reimbursement rates (the range of NCMS index from the data) lead to an increased in outpatient admission probability of 16%. It also increased inpatient admission, but this was not statistically significant. Unsurprisingly, they also found that enrolees are more likely to choose providers with more generous reimbursements. Meanwhile, Babiarz, et al. (2010) reported that NCMS did not change overall medical care use, but it might have redirected patients from larger and more specialised facilities towards village clinics which could be perceived as a favourable outcome.

For a more recent reform that took place in 2007, Chen, et al. (2014) found that URBMI marginally increased the probability of seeking medical care in inpatient and outpatient care by 1.8% and 1.7% respectively. A similar finding was also reported by Liu and Zhao (2014) using different datasets and estimation methods.

Furthermore, Liu, Wu, and Liu (2014) also reported positive effect of three schemes (GMI, UEBMI, and NCMS) on utilisation rates, but they admitted that their method (Structural Equation Modelling [SEM]) is not appropriate for drawing causal effects. Overall, this review agrees with the previous review (Acharya, et al., 2012); Health insurance reform in China tends to deliver positive impact on utilisation of health care either by increasing overall medical visits or substituting specialised visits with primary care visits.

Vietnam is also one of the countries which experiments with different schemes for different target populations. In principal, there are two different schemes: the compulsory scheme, which covers formal workers in both government and large companies; students in universities and colleges; and the voluntary scheme which covers near poor people. Children under the age of 6 and the poor population are covered with the compulsory schemes, but their premium are waived. Nguyen (2012) evaluated the voluntary scheme with propensity score matching and difference-in-difference-DID and compared it with instrumental variables and fixed effect. He reported that the voluntary scheme increased annual outpatient visits from 2.02 to 2.93 and annual inpatient visits from 0.11 to 0.18, on average. In addition, Guindon, et al. (2014) evaluated the contributory scheme and reported different patterns by target population. They found a positive effect on inpatient visits, but not on outpatient visits for poor people and students; and vice versa for children under the age of 6. However, Nguyen and Wang (2013) reported increased hospitalisations in secondary facilities, but a decreased for tertiary facilities for children under the age of 6. Meanwhile, even though it only partially solved for observables selection bias, Nguyen (2014) reported that insured people in compulsory schemes have on average 0.47 more outpatient visits than the uninsured. He further concluded that no moral hazard or adverse effect was observed for hospital visits. Overall, there is more consensus towards the positive effect of health insurance reform on utilisation of overall medical care in Vietnam.

In Colombia, the overall picture is leaning towards positive effect of health insurance on utilisation of either general medical care or maternal health services. Camacho

and Conover (2013) utilised administrative data and constructed a regression discontinuity model to evaluate the impact of the health reform on maternal health services. They found that the reform increases the probability of a mother to deliver in formal health care facilities. In addition, Miller et al. (2013) also constructed the fuzzy regression discontinuity from the household survey and reported increased outpatient visits and preventive visits (such as, growth monitoring and well-care visits), but no observed effect on hospitalisation. They also found that insured mothers were no more likely to have harmful maternal behaviours, such as smoking and drinking, than the uninsured.

There is a big interest among researchers in Colombia to evaluate the moral hazard effect under their current health care reform. Trujillo, et al. (2010) reported that there is no evidence for people in contributory schemes to avoid preventive measures. Meanwhile Hassan, et al. (2013) evaluated the impact of health insurance by using the two-stage nonlinear method (similar to bi-probit model, but with more relaxed assumption in its distribution) and they found that people in the subsidised scheme were more likely to use inpatient care and less likely to use preventive care, which suggests a strong moral hazard effect.

In Georgia, three studies reported the impact of health insurance for poor people on utilisation. One study with a robust method found that the insured under the new scheme were nine times more likely to utilise acute surgeries than the uninsured (Hou and Chao, 2011). However, two other studies with weaker methods showed smaller effect on utilisation though the overall conclusion seems to favour a positive effect (Gotsadze et al., 2015; Zoidze et al., 2013). However, it is worth noting that Hou and Chao (2011) used the data collected just 6 months after reform while the other two studies used more recent datasets in 2010. It is possible the strong effect observed in the first year subsided after longer periods.

All included studies evaluating health insurance in Ghana suffer from weaker methods to overcome selection bias issues. Overall, the health insurance increased utilisation on outpatient, inpatient, and maternal health services (Abrokowah, et al.,

2014; Blanchet, et al., 2012; Dixon et al., 2014; Fenny et al., 2015). Meanwhile, studies evaluating the current reform in Rwanda showed strong positive effect on utilisation with mixed strength of evidence (Lu et al., 2012; Dhillon, et al., 2012). The similar mixed evidence was also observed in Thailand (Limwattananon, et al. (2015); Papiemras, et al., 2011).

Robyn, et al. (2012a) used cluster randomisation study to evaluate the impact of community-based health insurance in Burkina Faso and they found that the insured were 33% more likely to seek treatment, but this effect was not significant. They argued that this weak evidence could be caused by a very low enrolment rate (10%), compounded by the misplaced incentives for providers. Also, the insurance did not provide comprehensive medical benefit for its beneficiaries. In another paper, Robyn, et al. (2012b) reported that the health insurance did not have strong role in reducing self-treatment. They also found no evidence for adverse selection in terms of chronic conditions. This could also mean that people perceive the services provided under the new reform as inferior to self-treatment or private care so they are less likely to join the scheme.

For the rest of the studies, one country is represented by one study only. Sood et al. (2014) utilised the phased roll out of the community based insurance in India and they found positive effect, but it was not statistically significant. Sparrow, et al. (2013) reported that the health insurance for the poor in Indonesia increased utilisation rate by 0.062 visits per person per month. Alkenrack and Lindelow (2015) reported increased probability of having inpatient visits among the insured compared with the uninsured in Lao, but their method did not consider the unobservable selection bias. Chami, et al. (2014) evaluated the health insurance in Tanzania and found that the insured are more likely to seek care and less likely to experience a delay in seeking medical treatment, but their study has a less convincing method to address the selection bias. Finally, Makhloufi, et al. (2015) reported a positive effect on utilisation for both mandatory and subsidised schemes compared to the uninsured in Tunisia.

### 5.3.4 Financial protection

Overall, the evidence on the impact of health insurance on financial protection is less clear-cut than that for utilisation (see Figure 5-3 and Table 5-2). Thirty four of the 46 studies reported the impact on the level of out-of-pocket health expenditure. Among those 34 studies, 17 studies found a positive effect (i.e. a reduction in out-of-pocket expenditure), 15 studies found no statistically significant effect, and two studies – from Indonesia (Sparrow, Suryahadi and Widyanti, 2013) and Peru (Bernal, Carpio and Klein, 2014) – reported a negative effect (i.e. increase in out-of-pocket expenditure).

The second most popular financial protection measure is the probability of incurring catastrophic health expenditure defined as OOP exceeding a certain threshold percentage of total expenditure or income. Of the 14 studies in this review, nine reported reduction in the risk of catastrophic expenditure, three found no statistically significant difference, and two found a negative effect of health insurance. Only four studies reported sensitivity analysis to changes in the threshold level (Bernal, Carpio and Klein, 2014; Fink et al., 2013; Grogger et al., 2015; Sparrow, Suryahadi and Widyanti, 2013), though this did not affect the result qualitatively.

Another measure of financial protection has been the probability of impoverishment due to catastrophic health expenditure. Two studies have evaluated this outcome with different conclusions (Fan, Karan and Mahal, 2012; Aryeetey et al., 2016). Finally, four studies evaluated the effect on financial protection by assessing the impact of insurance on non-healthcare consumption or saving behaviour, such as non-medical related consumption (Bai and Wu, 2014), probability of financing medical bills via asset sales or borrowing (Babiarz et al., 2010), and household saving (Cheung and Padieu, 2013). Unfortunately, no clear pattern can be observed from those four studies.

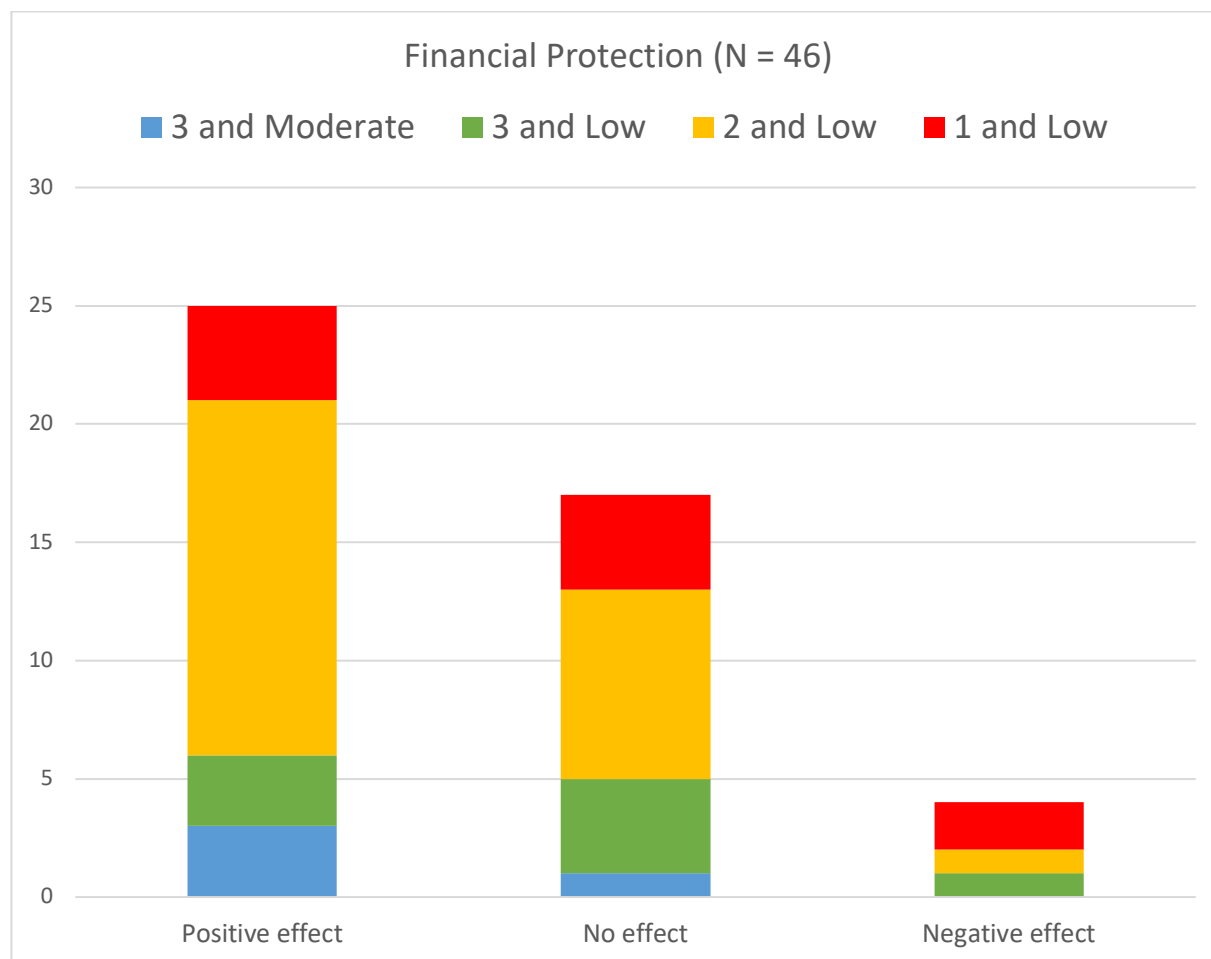


Figure 5-3 Summary of the impact of health insurance on financial protection

Table 5-2 Summary of studies reporting financial protection outcome (N=46)

Study	Country	Insurance*	Effect	QUEENS* *	GRADE†
(Parmar et al., 2012)	Burkina Faso	CBHI	+	2	Low
(Fink et al., 2013)	Burkina Faso	CBHI	+	3	Moderate
(Levine, Polimeni and Ramage, 2016)	Cambodia	CBHI	+	3	Moderate
(Babiarz et al., 2010)	China	SHI	+	2	Low
(Lu, Liu and Shen, 2012)	China	SHI	0	2	Low
(Cheung and Padieu, 2013)	China	SHI	+	2	Low
(Jing et al., 2013)	China	SHI	0	1	Low
(Bai and Wu, 2014)	China	SHI	+	3	Low
(Hou et al., 2014)	China	SHI	0	2	Low
(Liu and Zhao, 2014)	China	SHI	0	2	Low
(Liu, Wu and Liu, 2014)	China	SHI	0	1	Low
(Yuan et al., 2014)	China	SHI	0	2	Low
(Atella, Brugiavini and Pace, 2015)	China	SHI	+	1	Low
(Li et al., 2011)	China	SHI	0	2	Low
(Jung and Streeter, 2015)	China	SHI	+	2	Low
(Yang and Wu, 2015)	China	SHI	0	2	Low

(Camacho and Conover, 2013)	Colombia	SHI	0	3	Low
(Miller, Pinto and Vera-Hernandez, 2013)	Colombia	SHI	0	3	Low
(Yilma et al., 2015)	Ethiopia	CBHI	+	1	Low
(Zoidze et al., 2013)	Georgia	SHI	-	1	Low
(Gotsadze et al., 2015)	Georgia	SHI	0	1	Low
(Abrokwah, Moser and Norton, 2014)	Ghana	SHI	+	1	Low
(Brugiavini and Pace, 2015)	Ghana	SHI	0	2	Low
(Aryeetey et al., 2016)	Ghana	SHI	+	2	Low
(Fan, Karan and Mahal, 2012)	India	SHI	+	3	Low
(Sheth, 2014)	India	CBHI	+	3	Low
(Sood et al., 2014)	India	SHI	+	2	Low
(Raza et al., 2016)	India	CBHI	0	3	Moderate
(Aji et al., 2013)	Indonesia	SHI	+	2	Low
(Sparrow, Suryahadi and Widyanti, 2013)	Indonesia	SHI	-	2	Low
(Alkenbrack and Lindelow, 2015)	Lao	CBHI	0	2	Low
(Galarraga et al., 2010)	Mexico	SHI	+	2	Low
(Sosa-Rubi, Salinas-Rodriguez and Galarraga, 2011)	Mexico	SHI	+	2	Low
(Wirtz et al., 2012)	Mexico	SHI	+	2	Low
(Avila-Burgos et al., 2013)	Mexico	SHI	+	1	Low
(Grogger et al., 2015)	Mexico	SHI	+	3	Moderate
(Bernal, Carpio and Klein, 2014)	Peru	SHI	-	3	Low
(Lu et al., 2012)	Rwanda	CBHI	+	2	Low
(Koch and Alaba, 2010)	South Africa	SHI	-	1	Low
(Limwattananon et al., 2015)	Thailand	SHI	+	2	Low
(Makhloufi, Ventelou and Abu-Zaineh, 2015)	Tunisia	SHI	0	1	Low
(Sepehri, Sarma and Oguzoglu, 2011)	Vietnam	SHI	+	2	Low
(Nguyen, 2012)	Vietnam	SHI	0	3	Low
(Nguyen and Wang, 2013)	Vietnam	SHI	+	2	Low
(Palmer et al., 2015)	Vietnam	SHI	0	3	Low
(Nguyen, 2016)	Vietnam	SHI	+	2	Low

\* SHI = Social Health Insurance; CBHI = Community-based Health Insurance

\*\* Queens score: 1 = high risk; 2 = moderate risk; 3 = low risk

† Grade score: Low = low quality; Moderate = moderate quality; High = high quality

As shown in previous sub-section, studies in China have the biggest share among the included studies. There are eight studies evaluating NCMS, one study for URBMI, and one study for all four schemes. Liu and Zhao (2014) found that the insured under URBMI scheme were more likely to have higher out-of-pocket (OOP) health

expenditure, but this effect was not statistically significant. They also found inequality in terms of OOP health inequality disfavours the poor population. Lu, Liu, and Shen (2012) and Cheng, et al. (2015) also found a similar pattern when they evaluated the impact of NCMS on OOP health expenditure using different datasets and estimation methods. Hou, et al. (2014) further elaborated the pattern by breaking down the OOP into outpatient and inpatient expenditure. They found that a 1 percent increase in NCMS generosity index leads to an increase in total spending and OOP for inpatient care, but not for outpatient care in the village level. However, at the household level they found a different pattern in which NCMS increases OOP share for outpatient care but had no effect on inpatient care. In addition, Yang, et al. (2015) compared the OOP before and after the reimbursement and they found that the insured are associated with higher OOP total health spending pre-and post-reimbursement, even though the significant coefficient only appears in pre-reimbursement. Even the study with the lowest quality score among the studies in China found the insignificant increased OOP effect for NCMS beneficiaries, but significantly reduced OOP effect for UEBMI and URBMI beneficiaries.

On the other hand, Lu, Liu, and Shen (2012) reported that the insured are associated with reduced OOP even though this effect was not significant, which also in agreement with a study by Cheng and Padieu (2013). Meanwhile, only Babiarz, et al. (2010) reported a significant reduced OOP health expenditure by 19% among the insured in NCMS scheme compared to the uninsured.

Other measures of financial protection also emerge among the included studies; one of the most studied is the probability of incurring catastrophic health expenditure (CHE). Babiarz, et al. (2010) reported that the insured in the NCMS scheme is associated with a 2% point reduced the likelihood of incurring CHE. Meanwhile, Lu, Liu, and Shen (2012) reported no conclusive direction and no significant effect of NCMS on the probability of incurring CHE.

Another different method is the probability of impoverishment due to catastrophic health expenditure. Even though the effect is favourable, the study suffers from a low-



quality score (Jing, et al., 2013). Finally, some studies also evaluated the financial protection through the impact on other consumption or saving behaviour. Bai and Wu (2014) found that participation in NCMS increase the nonmedical-related consumption by more than 5% with stronger effect among people reporting worse self-reported health status. Babiartz, et al. (2010) reported reduced probability of financing medical bill by asset sales or borrowing by 2 percent among NCMS beneficiaries. Cheng and Padieu (2013) reported that NCMS beneficiaries in third quintiles experience reduced household saving, but this effect is not observed among the poorest nor the richest.

Overall, there is more evidence to conclude that NCMS does not provide adequate financial protection through the reduction in OOP health expenditure. The conclusion for other measures is less convergent thus it is desirable to have more studies with stronger methodology in the future as the use of OOP reduction measures has been criticised for not providing a comprehensive picture of the financial protection effect.

In Burkina Faso, Gunther, et al. (2013) utilised the cluster randomised study for the introduction of CBHI in one rural district. They found that the insured are associated with 30% reduction in the likelihood of incurring CHE compared to the uninsured. Furthermore, Parmer, et al. (2012) reported that CBHI increased household assets among the insured in Burkina Faso.

In India, the favourable effect is more prominent for expenditure in inpatient care and drug spending. Fan, et al. (2012) evaluated the impact of social health insurance in two different areas and different times and they found that the insured is associated with reduced OOP spending, but the pattern was varied between two study areas; reduced OOP for inpatient but not for outpatient in one area and reduced OOP for drug spending but not for inpatient in another area. They also found no effect on any measure of impoverishment from any area. Meanwhile, Sood, et al. (2014) evaluated a different insurance scheme for poor people in rural areas and they found 34% reduction in OOP for inpatient care among the insured population.

In Vietnam, the evidence indicates that greater protection is provided from the subsidised schemes rather than the voluntary ones. Nguyen (2012) reported that the insured among voluntary scheme experience reduced OOP, but this effect was not statistically significant. Using a different dataset but weaker methodology, Sepehri, et al. (2011) also found no impact of voluntary scheme on OOP spending, but they found a reduction of OOP by 16% among poor people who were covered by the subsidised scheme. In addition, Nguyen and Wang (2013) evaluated the impact of subsidised compulsory scheme for children under the age of 6 and they reported reduced probability of incurring CHE by 1.7% point compared to children 6-7 years who were excluded from the scheme and uninsured.

In Mexico, it is found that the overall favourable effect in financial protection is prominent, especially for drug expenditure. Galarraga, et al. (2010) using two different datasets with similar methods reported that the insured people are more likely to have reduced OOP spending for outpatient, inpatient, and drug expenditure and are less likely to incur CHE compared to the uninsured population and this effect still held when they repeated the analysis using another dataset, but with smaller magnitude. Meanwhile, Wirtz, et al. (2012) found a significant reduction effect for drug expenditure, but no significant effect on the share of drug expenditure spent from household available expenditure funds. Finally, Avilla-Burgos, et al. (2013) using weaker method and slightly different datasets found that patients with chronic conditions and insured with Seguro Popular are less likely to incur health expenditure compared to uninsured chronic patients.

In Indonesia, the evidence is more inconclusive as two studies with different datasets reach opposite conclusions. Sparrow, et al. (2013) used panel datasets from a national socioeconomic survey and found that the insured people under the Askeskin scheme are more likely to have larger OOP especially in urban areas compared to non-Askeskin people. Furthermore, the insured people have a higher incidence of incurring CHE by 15%. Meanwhile, Aji, et al. (2013) used a different panel dataset

and found that Askeskin reduced OOP spending among its beneficiaries 34% lower compared to non-Askeskin people.

In Georgia, the evidence comes from two low quality data, thus no definite conclusion can be drawn. Zoidze et al. (2013) found that poor people under the new scheme are associated with reduced OOP spending for total health expenditure and inpatient care expenditure. However, they also found an increased probability to incur CHE among the insured. In addition, Gotzadze (2015) also found the same even though it is marginally significant.

### 5.3.5 Health status

Improving health is one of key aims of health insurance, yet very few studies have thus far attempted to evaluate this. I identified 12 studies, with considerable variation in the precise health measure considered (see Table 5 and 6). There is some evidence of positive impact on health status: nine studies found positive effect, one study reported negative effect, and two studies reported no effect.

In Burkina Faso, there are two studies which took place in the same district, Nouna, but yield different conclusion. Gunther, et al. (2013) used the rollout of insurance to evaluate the impact of CBHI on mortality rates and they found that the scheme is associated with increased general mortality rates. After stratifying the analysis by the age, they found that the insured elderly has 30% higher mortality rate compared to the uninsured in the same age group. Meanwhile, they found a decreasing trend of under-5 mortality rates from 170 deaths per 1000 in the insured group to 103 deaths per 1000 in the uninsured group. By using different methods and datasets, Schoeps, et al. (2015) reported almost similar findings. Among 33,500 children, they found that the insurance is associated with decreased mortality rate (Hazard Ratio: 0.54, 95%CI = 0.43 to 0.68). However, their cox regression model cannot fully consider some unobserved bias that may influence the insurance status, which is likely to happen as the reported enrolment rate was very low. They attempted to control this

bias by using vaccination coverage as the instrument for insurance status, but no assumption checks were reported in their paper.

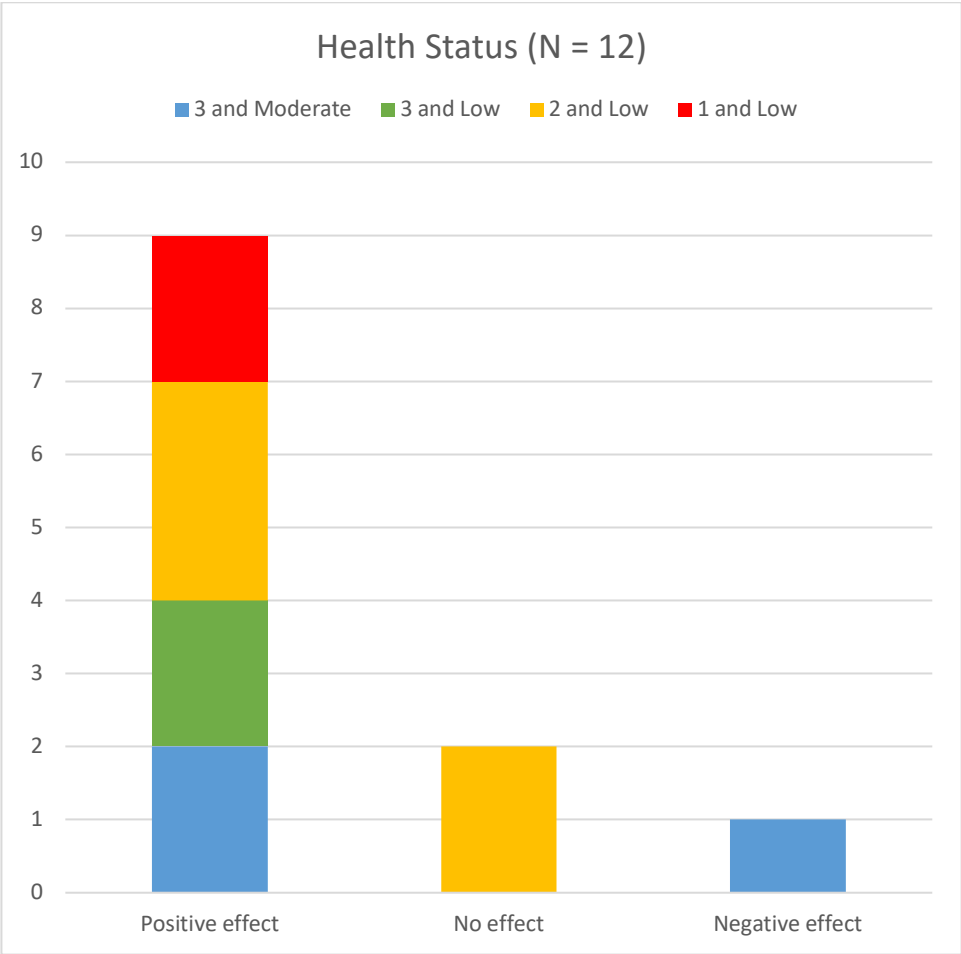


Figure 5-4 Summary of the impact of health insurance on health status

Table 5-3 Summary of studies reporting health status (N=12)

Study	Country	Insurance	Effect	QUEENS	GRADE	Chosen outcomes
(Fink et al., 2013)	Burkina Faso	CBHI	-	3	Moderate	Child and adult mortality
(Levine, Polimeni and Ramage, 2016)	Cambodia	CBHI	+	3	Moderate	Health index
(Chen and Jin, 2012)	China	SHI	0	2	Low	Child and maternal mortality
(Cheng et al., 2015)	China	SHI	0	2	Low	Adult mortality
(Peng and Conley, 2016)	China	SHI	+	2	Low	Malnutrition and food consumption
(Camacho and Conover, 2013)	Colombia	SHI	+	3	Low	Low birth weight and newborn health status
(Miller, Pinto and Vera-Hernandez, 2013)	Colombia	SHI	+	3	Low	Acute illness
(Sood et al., 2014)	India	SHI	+	2	Low	Adult mortality
(Pfutze, 2014)	Mexico	SHI	+	2	Low	Child mortality
(Pfutze, 2015)	Mexico	SHI	+	1	Low	Miscarriages prevalence
(Hendriks et al., 2014)	Nigeria	CBHI	+	1	Low	Blood pressure
(Quimbo et al., 2011)	Philippines	SHI	+	3	Moderate	CRP-positive level and wasting

\* SHI = Social Health Insurance; CBHI = Community-based Health Insurance

\*\* Queens score: 1 = high risk; 2 = moderate risk; 3 = low risk

† Grade score: Low = low quality; Moderate = moderate quality; High = high quality

In China, the evidence tends to show no improvement in mortality rate, especially for the adult population. Cheng et al. (2015) used panel data from 2005-2008 and PSM-DID method and found that there is no significant effect of NCMS on 3-year mortality rates among elderly enrollees. They also found a positive effect on elderly enrollees' activities of daily living and cognitive function, but this has not led to better self-assessed general health status. Furthermore, Chen and Jin (2012) used the 2006 China Agriculture Census and also found that NCMS had no effect on reducing the incidence of child and maternal mortality rate. Finally, Liang and Lu (2014) used SF-36 variables in general, psychological, and physical health and reported some beneficial effects on the elderly population, but they did not control for selection bias.

In Colombia, the evidence leads to an improvement of child health after the introduction of subsidised health insurance. By using the regression discontinuity (RD) method to analyse registry data, Camacho and Conover (2013) reported that the insurance is associated with lower incidence of low birth weight by 1.7-3.8 percentage points. Furthermore, Miller, et al. (2013) used fuzzy RD design to analyse household surveys and found that SR enrolment is associated with 1.4 fewer child days absent from usual activities due to illness in the past month.

Other studies in different countries also tend to report positive effect of health insurance on health status. Sood, et al. (2014) reported lower mortality rate for conditions covered by the scheme in India. Pfütze (2014) used a Weighted Exogenous Sampling Maximum Likelihood approach to control for censored selection bias in birth registry in which births of surviving children are more likely to be observed than births of non-surviving ones. He found that the subsidised health insurance program in Mexico is associated with a significant large negative effect on infant mortality. The mortality reduction is expected to be 5 out of 1,000 (or 0.5%) for the population at large and by around 7 out of 1,000 (0.7%) for the scheme's target population. In the Philippines, Quimbo et al. (2011) used a DID approach to analyse data from a randomised policy experiment known as the Quality Improvement Demonstration Study and estimated a 9–12 and 4–9 percentage point reduction in the likelihood of wasting and having an infection, respectively, as measured by a common biomarker C-reactive Protein. Finally, Hendriks, et al. (2014) used DID approach and intention to treat analysis to analyse household surveys in Nigeria and found that CBHI program is associated with a significant decrease in blood pressure in a hypertensive population in rural Nigeria.

## **Section 5.4 Discussion**

I have identified a total of 68 eligible studies over a period of six years – exactly double the amount of the studies identified by the previous seminal review by Acharya et al. over an approximately 60-year time horizon (1950 - July 2010). While similar search strategy and inclusion criteria are still retained, this review is different

from Acharya's review by the use of different approach of assessing the study quality. In this review, two quality assessment checklists are used to scrutinise the study methodology without disregarding the heterogeneity among non-experimental design. While GRADE has been widely used to grade the quality of evidence from a randomised study, QuEENS gives a more detailed approach to assess the strength of evidence from a non-randomized study.

#### 5.4.1 Overall effect

While Acharya et al. (2013) found weak evidence that health insurance yields higher utilisation, I have found stronger and more consistent evidence of positive effects of health insurance on health care utilisation. This pattern has been echoed by other reviews (Comfort et al., 2013; Giedion et al., 2013; Spaan et al, 2012; Ekman et al., 2004) except that no previous reviews have reported any negative effect on utilisation. In my review, I found one study in India which evaluated the community-based health insurance (CBHI) in one part of India (Sheth, 2014). The author suggested that the insurance may reduce the consumption and expenditure of health care which may be an indication of improved health status of the insured. However, the author does not explore the possibility of low quality services that has been suggested in other CBHI evaluation studies (Robyn et al., 2012; Raza et al., 2016). It is at least conceivable that the insured decided not to use any formal health care services and turned to traditional medicine which is still widely used in India (Payyappallimana, 2010).

I also have found that there is less clear evidence to indicate a positive effect of health insurance on financial protection, echoing the findings from previous reviews (Acharya et al., 2012; Giedion et al., 2012). Restricting the evidence base to the small subset of randomised studies, the effects on financial protection appear more consistently positive, i.e. three cluster randomised studies (Levine, Polimeni and Ramage, 2016; Grogger et al., 2015; Fink et al., 2013) showed a decline in OOP expenditure and one randomised study (Raza et al., 2016) found no significant effect.

Besides the impact on utilisation and financial protection, this review identified a number of good quality studies measuring the impact of health insurance on health outcomes. Twelve studies were identified (i.e. twice as many as Acharya's review), nine of which showed a beneficial health effect. This holds for the subset of papers with stronger methodology for tackling selection bias (Levine, Polimeni and Ramage, 2016; Camacho and Conover, 2013; Miller, Pinto and Vera-Hernandez, 2013; Quimbo et al., 2011). However, Acharya et al. (2012) did not report any paper showing adverse health impacts, I identified one such study that also applied a particularly strong method (i.e. a clustered randomised trial of the rollout of the CBHI in Burkina Faso (Fink et al., 2013). This study attributed the increased mortality among the elderly in the insured population to the negative incentives embedded in the capitation payment system, arguing that it may have upset the providers by taking away their regular income from user charges and consequently delivering worse quality of services.

In cases where a health insurance programme does not have a positive effect on either utilisation, financial protection, and health status, it is particularly important to understand the underlying reasons which will be discussed below.

#### **5.4.2 Possible explanation of heterogeneity**

##### **1. Payment system**

Heterogeneity of the impact of health insurance may be explained by differences in health systems and/or health insurance programmes. Robyn et al. (2012) and Fink et al (2013) argued that the lack of significant effect of insurance in Burkina Faso may have been partially influenced by the capitation payment system. As the health workers relied heavily on user fees for their income, the change of payment system from fee-for-services to capitation may have discouraged provision of high quality services. If enrolees perceive the quality of contracted providers as bad, they might delay seeking treatment, which in turn could impact negatively on health.



Several studies from China found the utilisation of expensive treatment and higher-level health care facilities to have increased following the introduction of the insurance scheme (Cheng et al., 2015; Yang and Wu, 2015; Liu and Zhao, 2014; Lu, Liu and Shen, 2012) . A fee-for-service payment system may have incentivised providers to include more expensive treatments ( Yang and Wu, 2015; Hou et al., 2014; Liu, Wu and Liu, 2014). Recent systematic reviews suggested that payment systems might play a key role in determining the success of insurance schemes (Eijkenaar et al., 2013; Robyn et al., 2013), but this evidence is not too strong, as most of the included studies were observational studies not controlling for selection bias sufficiently.

## **2. Uncovered essential item**

Sood et al. (2014) found no statistically significant effect of community-based health insurance on utilisation in India. They argued that this could be caused by their inability to specify the medical conditions covered by the insurance, causing dilution of a potential true effect. In other countries, transportation costs (Nguyen, 2012) and treatments that were not covered by the insurance (Alkenbrack and Lindelow, 2015; Sparrow, Suryahadi and Widyanti, 2013) may explain the absence of a reduction in out-of-pocket health expenditures.

## **3. Methodological differences**

Two studies in Georgia evaluated the same programme but with different conclusions (Zoidze et al., 2013; Hou and Chao, 2011). This discrepancy may be explained by the difference in the estimated treatment effect: one used average treatment effect (ATE), finding no effect, and another used average treatment effect on the treated (ATT), reporting a positive effect. ATE is of prime interest when policymakers are interested in scaling up the programme, whereas ATT is useful to measure the effect on people who were actually exposed to insurance (Loi and Rodrigues, 2012).

#### **4. Duration of health insurance**

I also found that the longer an insurance programme has been in place prior to the timing of the evaluation, the higher the odds of improved health outcomes. It is plausible that health insurance would not change the health status of population instantly upon implementation (Giedion et al., 2013). While there may be an appetite among policymakers to obtain favourable short term assessments, it will be important to compare the impact over time, where feasible.

#### **5.4.3 Moral hazard**

Acharya et al (2012) raised an important question about the possibility of a moral hazard effect as an unintended consequence of introducing (or expanding) health insurance in LMIC. I found seven studies exploring ex-ante moral hazard by estimating the effect on preventive care. If uninsured individuals expect to be covered in the future, they may reduce the consumption of preventive care or put less investment on healthy behaviours (de Preux, 2011; Dave and Kaestner, 2009). The overall evidence cannot suggest a definite conclusion considering the heterogeneity in chosen outcomes. One study found that the use of a self-treated bed nets to prevent malaria has declined among the insured group in Ghana (Yilma, Van Kempen and De Hoop, 2012) while two studies reported an increase in vaccination rate (Bernal, Carpio and Klein, 2014) and the number of prenatal care visits (Abrokwah, Moser and Norton, 2014; Bernal, Carpio and Klein, 2014) among the insured group. Meanwhile, another study reported no evidence that health insurance encouraged unhealthy behaviour or reduction of preventive efforts in Thailand (Ghislandi, Manachotphong and Perego, 2015).

Two studies from Colombia found that the insured group is more likely to increase their demand for preventive treatment (Miller, Pinto and Vera-Hernandez, 2013; Trujillo et al., 2010). As preventive treatment is free for all, both authors attributed this increased demand to the scheme's capitation system, incentivising providers to promote preventive care to avoid future costly treatments (Peckham and Disclaimer, 2014). Another study in Colombia, however, found an opposite effect but this study

looked into a different health insurance programme in Colombia (Hassan, Jimenez and Montoya, 2013).

#### **5.4.4 Type of insurance**

In my inclusion criteria, I distinguished two type of health insurance based on how it is financed: social health insurance (SHI) and community based health insurance (CBHI). Among the included studies, I found 13 studies about CBHI and two of them are able to utilize cluster randomized study. Also, there are 40 studies studying SHI but only one study using cluster randomized study. When the studies are grouped based on CBHI and SHI, there is only slightly different pattern seen in financial protection and health outcome. Similar pattern of overall positive effect on utilisation can be observed for both groups. CBHI tends to show more favourable effect on financial protection; in fact, all studies reporting unfavourable effect are in SHI group only. However, only CBHI group that has one study reporting negative effect on health outcome. It does not mean that one system is better than the other one. As I have discussed it earlier, the choice of provider payment system may play more distinctive role in determining the success of the scheme in decreasing out-of-pocket health expenditure.

#### **5.4.5 Study limitations**

This review includes a large variety of study designs and indicators for assessing the multiple potential impacts of health insurance, making it hard to directly compare and aggregate findings. For those studies that used a control group, the use of self-selected controls in many cases may have biased the results. Second, for a better understanding of the channels between health insurance and relevant outcomes, there is a need to go beyond quantitative evidence alone, and combine the quantitative findings with qualitative insights. This is particularly important when trying to interpret some of the counterintuitive results encountered in some studies.

## **Section 5.5 Conclusion**

Despite heterogeneity of the studies in this review, the impact of different health insurance schemes in many countries on utilisation generally shows a positive effect. This is aligned with the supply-demand theory in which the health insurance decreases the price of health care services resulting in increased demand. Nevertheless, given the differences in findings between studies, it is difficult to draw an overall conclusion about the impact of health insurance on financial protection. Furthermore, the impact on health status suggests a promising positive effect, but more studies from different countries are required. In the next chapter, drawing from the studies identified from this chapter I will explore the impact evaluation methods that have been applied to estimate the causal relationship of health insurance. This method review is important as a guide for me to choose the most appropriate method to evaluate the JKN programme in Indonesia.

# Chapter 6 Methods for evaluating health insurance programmes

## Section 6.1 Introduction

This chapter reviews the methods for measuring the impact of health insurance programmes on access to health care, financial protection and health outcomes. I will begin by discussing common regression approaches to dealing with non-normally distributed outcomes variables: binary outcomes (for example, whether a person had any outpatient visits in the past 4 weeks or the proportion of hypertensive people who had their blood pressure controlled), count data (for example, number of doctor visits) and expenditure data. Since the rollout of the JKN programme was not randomised, a linear regression model is not sufficient to estimate the treatment effect due to selection bias. I will briefly discuss the concept of selection bias in health insurance and several alternative statistical methods for controlling selection bias, drawing upon the evidence from existing health insurance evaluation studies identified in Chapter 5.

## Section 6.2 Regression methods for non-normally distributed variables

### 6.2.1 Binary variables

The linear regression model can be extended to include a binary variable as its dependent variable. This is called a linear probability model (LPM) because the response probability is still linear in the parameter of covariates. Assuming that we have a binary dependent variable  $y = 1$  if it is a success and  $y = 0$  if it is a failure:  $x =$  independent variable as a covariate;  $\alpha =$  the intercept;  $\beta =$  the slope of the covariate; and  $e =$  the error term, we can write a simple regression model:

*Equation 6-1*

$$y = \alpha + \beta x + e$$

Thus, the interpretation of  $\beta$  in Equation 6-1 is the predicted change in the probability of success when  $x$  changes by one unit. However, LPM has mainly two disadvantages: the predicted probability of  $y$  is not bounded between zero and one, and the partial effects of any covariate are constant (Wooldridge, 2013). To overcome this limitation, we can use the binary response model. In a binary response model, it is assumed that the value of  $y$  is motivated by a latent continuous variable ( $y^*$ ) which is unobservable (see Eq. 6-2). The primary objective is to explain the effects of the independent variables ( $x$ ) on the response probability  $P(y = 1|x)$ , which can be estimated by specifying a distribution function bounded between zero and one, such as normal distribution (i.e. the probit model) or logistic distribution (i.e. the logit model) (Jones, 2007).

*Equation 6-2*

$$y^* = \alpha + \beta x + e; \text{ where } y = 1 \text{ if } y^* > 0, \text{ or zero otherwise}$$

*Equation 6-3*

$$P(y = 1|x) = P(y^* > 0|x) = G(\alpha + \beta x)$$

Both the logit and probit models are fairly symmetrical but the logit model is more sensitive to the extreme value that the conditional probability approaches 0 or 1 at a slower rate in logit than in probit (Gujarati, 2011). In their application, LPM, logit and probit models often lead to a similar conclusion (Aldrich and Nelson, 1984). However, LPM should not be used if we are interested in obtaining a prediction and more caution is warranted if we wish to give the correct interpretation of the interaction term in either probit or logit (Ai and Norton, 2003).

The choice between logit and probit has been discussed elsewhere (Eugene and Refik, 2005). While LPM has more intuitive and easier to interpret, the interpretation for logit and probit should be done more carefully to avoid misleading conclusions (Hoetker, 2007). Firstly, the slope's coefficient no longer has a marginal effect interpretation. It is advisable to calculate the partial effect at the average (PEA) which is the marginal effect at the mean of covariates (Wooldridge, 2013), but this is not an

average effect. Other alternatives are to calculate the average partial effect (APE) which is defined as the response for each observation and the average of those responses (Train, 1986; Wooldridge, 2013) or to calculate the effect for several sets of relevant values of the variables (Hoetker, 2007). As a rough guide to comparing the coefficient in probit, logit and LPM, we can multiply the probit coefficients by 1.6, or multiply the logit estimates by 0.625. Secondly, comparisons of logit and probit across groups are not straightforward because the residual variances differ across groups (Allison, 1999). It is advisable to correctly adjust the slope coefficients to consider the residual differences (Allison, 1999) or to use heterogeneous choice models (Williams, 2009). Lastly, probit and logit do not have a goodness to fit property directly related to the R-squared as the LPM does (Hoetker, 2007). In conjunction, there are many choices of Pseudo-R-squared which have been developed to mimic the nice property of R-squared (Wooldridge, 2013). To summarise, in application we can run the three models but compare the findings with caution. As Aldrich and Nelson (1984, p. 79) argued, there is no superior choice between probit and logit:

*“The assumptions that underlie either probit or logit, beyond that specifying the relation between the mean of Y and X, are really quite similar to, and no more restrictive than, the remaining Gauss-Markov assumptions in OLS regression. Thus, the use of probit or logit is no more restrictive than is OLS in the general linear model.”*

### 6.2.2 Count data

As is often the case in public health research, a continuous variable may not always follow a normal distribution. A special case of this variable is called count data, where the variable contains a large mass of zeros and a right-skewed distribution (Jones, 2007). For example, in measuring the intensity of health care utilisation we can use the number of outpatient or inpatient visits within a certain period of time. This variable may contain many zero values indicating no use of care, which is quite prevalent in developing countries, and have a few very high values, pulling the mean to the right. Problematically, log transformation, which is a common approach to transforming continuous variables to get as close to normal distribution as possible,

cannot be applied to this variable as it contains many zero values. Therefore, it is necessary to model the expected value as an exponential function and find the correct distribution (Wooldridge, 2013). The most common distribution for count data regression is Poisson distribution. Other count data distributions are widely available, but if we are only interested in estimating the mean effects, the Poisson model is often adequate (Wooldridge, 2013). If we are interested in estimating the probabilities, the excess number of zeros and over-dispersion issues need to be considered when choosing the most appropriate distribution (Jones, 2007).

The negative binomial model can be used to relax the equal dispersion property of Poisson distribution. The zero-inflated model adds an additional probability of observing zero by avoiding the assumption of the same mean function for all responses. Alternatively, it is possible to separate the probability functions into the decision to participate and the positive values of the count data by using the Hurdle model. An effective framework for selecting econometric techniques for modelling the relationships between health insurance and count data variables is discussed elsewhere (Hidayat and Pokhrel, 2010; Cameron and Trivedi, 2010), but generally none of the above models are appropriate in the presence of endogeneity. The Poisson model is therefore adequate for exploring count data variables (for example, the number of outpatient or inpatient visits in Chapter 7) before moving to a more sophisticated analysis.

### **6.2.3 Health expenditure**

When analysing health care expenditure with a large proportion of zeros, a common problem is the difference between the actual outcome and the potential outcome. The actual outcome is a fully-observed variable. Zero values for actual health expenditure implies that zero costs were spent. These actual zero values can be seen as corner solutions because individuals cannot have negative health expenditures (Cameron and Trivedi, 2010). If many observations have zero expenditures, then the econometric challenge is to model these corner solutions.



In contrast, the potential outcome is a latent variable that is only partially observed. The non-zero values are assumed to be true observations of the potential outcome, but zero values indicate observations for which the potential outcome is missing (latent). The zeros do not represent zero values for the potential outcome. One possible interpretation of potential health expenditure is that for a person with zero actual expenditure, there is a latent positive expected expenditure that would have been incurred if the person had sought any health care (Dow and Norton, 2003). This is often called a care-seeking selection. For example, if a person with zero actual expenditure had been examined by a doctor, the doctor's perception of unmet health care needs could have led to procedures costing a sum of money. In this case, the latent potential expenditure would be positive, instead of zero as in the actual expenditure.

There are myriad models available for the analysis of health expenditure, but it is important to be clear about whether we are interested in actual outcomes or potential outcomes. In this thesis, health expenditure is assumed to be a potential outcome because access to health care is not universal, and financial barriers to seeking care are still very important in Indonesia, compared to developed countries where much of the health expenditure literature favours actual outcomes (Dow and Norton, 2003). It is more plausible in Indonesia to state that once people seek care, they are more likely to spend money to pay for clinic or hospital fees and prescription fees.

A two-part model (2PM) can be used to analyse health expenditure with care-seeking selection by assuming that the care-seeking mechanism and the amount of money spent for health care may be modelled using two separate processes (Duan et al., 1984). In other words, it permits the zeros and non-zeros to be generated using a different model. The zeros are typically handled using a model for the probability of a positive outcome. For instance, in explaining individual OOP health expenses, the first part determines the probability of non-zero expenditure, while the second part models the positive expenditures. This model, therefore, is able to decompose the

effect into the part attributable to individuals starting to participate (called extensive margin), and the part attributable to already participating individuals (called intensive margin) (Staub, 2014).

Estimating the parameters of the two-part model is straightforward. The first part representing the probability of observing positive outcomes is modelled using a regression model for binary outcomes such as probit or logit. Next, the positive outcomes are modelled using a regression framework for a continuous outcome; for example, they can be modelled using OLS regression or a generalized linear model (GLM). The error terms in the two equations do not need to be independent to get consistent estimates. While it is common to use log transformation for analysing positive health care expenditure due to the expenditure's highly-skewed distribution, this specification does not always perform well. An empirical paper studying the performance of the various specifications for health care costs has shown that the regression on log costs and the generalised linear model (GLM) with a log link perform poorly according to the link test and the Copas test (Jones, 2011). The poor performance of regression on log costs has been echoed by other authors using different datasets but similar performance criteria (Hill and Miller, 2010; Deb and Burgess, 2003). Furthermore, using log-transformed costs and applying Duan's smearing estimator is susceptible to bias if the error term on the log scale is heteroscedastic (Jones, 2011).

More recently, researchers have used the GLM framework to model positive health expenditure using a nonlinear transformation of a linear index function directly (Jones, 2011). Generalised Linear Models (GLMs) have become the dominant approach to modelling health care costs in the literature when there are unknown forms of heteroscedasticity (Jones, 2011; Buntin and Zaslavsky, 2004; Manning and Mullahy, 2001; Mullahy, 1998). These models specify a distribution function (for example, Gamma, Poisson or Gaussian) that reflects the relationship between the variance and the raw-scale mean functions and a link function that relates the conditional mean of medical costs to the covariates. GLM estimates are performed on the raw medical cost scale, so there is no need for retransformation as is the case

with log transformation in OLS. Another advantage is that this approach allows for heteroscedasticity through the choice of the distribution function (Mora, Gil and Sicras-Mainar, 2015). It is important to note that in the analysis of health expenditure, GLM is applied to model non-zero expenditure excluding the zeros because GLM is used to model the second part of the two-part model.

### **Section 6.3 Selection bias**

Programme evaluation has been of interest to many researchers for reporting on the effectiveness of a public policy to policymakers. In theory, programme evaluation has a similar motivation to medical treatment research. The fundamental difference between those two lies in how the causal relationship can be inferred from the evidence. The gold standard for medical research is the randomised control trial, in which the treatment is randomly assigned to the participants. For example, in a drug trial, patients are randomised into one of the groups; one group is given a trial treatment and another group is assigned to receive a placebo or usual treatment. The treatment assignment process has to be exogenous to ensure that any observed effect between the treated and control groups can only be caused by the difference in the treatment assignment. Unfortunately, this ideal scenario is often not feasible in a public policy setting. According to the updated review in Chapter 5, within the last five years there have been only three papers which have been able to conduct a randomised study to evaluate the impact of health insurance programmes in developing countries (Quimbo et al., 2011; Robyn et al., 2012; Fink et al., 2013;). The overview in Chapter 4 also identified a limited number of papers as well (Gnawali et al., 2009; King et al., 2009; Kraft et al., 2009; Thornton et al., 2010). Policymakers may believe in the value of an intervention regardless of its actual evidence base, or they may believe that the intervention is beneficial and that no one in need should be denied it. In addition, policymakers are inclined to demonstrate the effectiveness of an intervention that they want implemented in the most promising contexts, as opposed to random allocation (Bonell et al., 2011).

Consequently, most programme evaluators often have to deal with a non-randomised treatment assignment which may result in a selection bias problem. Selection bias

can be defined as the spurious relationship between the treatment and the outcome of interest due to the systematic differences between the treated and the control groups (Wooldridge, 2013). In the case of health insurance, an individual who chooses to enrol in the scheme may have different characteristics to an individual who chooses not to enrol. For example, sicker people are more motivated to enrol because they have predicted that the benefit of enrolling outweighs the cost. In the context of Indonesia, the JKN programme requires the potential enrollees to pay for the premium. This exhibits the classic adverse selection issue in insurance in which people who choose to enrol are more likely to have more health problems and use more medical care. Poor people are eligible to receive subsidies and their eligibility is determined by the proxy means test. This implies that the beneficiary of the subsidy was not given the choice to enrol or not. However, selection bias can still exist due to the fact that the list of eligible individuals may be contaminated; non-poor people may receive the subsidy. Individuals who are influential in the community, for example, the relatives of a local community leader, could persuade the local officials responsible for the verification of the eligibility list to include their names on the list. Thus, any confounding factors that are able to affect both the treatment decision and the outcome of interest need to be minimised to estimate an unbiased treatment effect. In general, omitting observable factors could be solved by identifying such factors within our data and including them in our model. However, controlling unobservable factors requires more advanced techniques and, sometimes, stronger assumptions. Based on the updated review in Chapter 6, various methods are quite popular among the health insurance evaluation studies, including propensity score matching (N = 8), difference-in-difference (N = 10), fixed or random effects of panel data (N = 6), instrumental variables (N = 12) and regression discontinuity (N = 6). In addition, some papers also employ a combination of two methods, such as difference-in-difference with propensity score matching (N = 10) and fixed effect with instrumental variables (N = 8).

In the next section, statistical methods for controlling either observable or unobservable factors are explained in more detail and their applicability in the Indonesian context will also be discussed. Since there are many possible statistical methods in the literature, this section will limit its scope to the range of common

methods found in the evaluation of health insurance programmes, as summarised in Table 6-1.

*Table 6-1 Summary of The Included Studies from the Updated Review (N = 68)*

<b>Study</b>	<b>Year</b>	<b>Method†</b>	<b>Type of Data</b>
<b>1. Propensity score matching (N = 8)</b>			
Koch and Alaba	2010	Propensity score matching	Cross-section
Blanchet et al	2012	Propensity score matching	Cross-section
Robyn et al	2012	Propensity score matching	Cross-section
Avilla-Burgos et al	2013	Propensity score matching	Cross-section
Nguyen	2014	Propensity score matching	Cross-section
Alkenrack and Lindelow	2015	Propensity score matching	Cross-section
Makhloufi et al	2015	Propensity score matching	Cross-section
Liao, Gilmour and Shibuya	2015	Propensity score matching	Cross-section
<b>2. Fixed effect, random effect or difference-in-difference (N = 16)</b>			
Babiarz et al	2010	Difference-in-difference	Repeated cross-section
Quimbo et al	2011	Difference-in-difference	Randomised
Sosa-Rubi, Salinas-Rodriguez and Galarraga	2011	Difference-in-difference	Panel Data
Jing et al	2013	Difference-in-difference	Repeated cross-section
Nguyen and Wang	2013	Difference-in-difference	Panel Data
Zoidze et al	2013	Difference-in-difference	Repeated cross-section
Hendriks et al	2014	Difference-in-difference	Panel Data
Sheth	2014	Difference-in-difference	Panel Data
Yuan et al	2014	Difference-in-difference	Panel Data
Gotsadze et al	2015	Difference-in-difference	Repeated cross-section
Panpiemras et al	2011	Fixed effect	Panel Data
Robyn et al	2012	Fixed effect	Randomised
Grogger et al	2015	Fixed effect	Panel Data
Yilma et al.	2015	Fixed effect	Panel Data
Nguyen	2016	Fixed effect	Panel Data
Sepehri et al	2011	Random effect	Panel Data
<b>3. Instrumental variables (N = 12)</b>			
Trujillo et al	2010	Instrumental variables	Cross-section
Lu, Liu and Shen	2012	Instrumental variables	Cross-section
Wirtz et al	2012	Instrumental variables	Cross-section
Cheung and Padieu	2013	Instrumental variables	Repeated cross-section
Fink et al	2013	Instrumental variables	Randomised
Hassan et al	2013	Instrumental variables	Cross-section
Chen et al	2014	Instrumental variables	Repeated cross-section
Brugiavini and Pace	2015	Instrumental variables	cross-section
Levine, Polimeni and Ramage	2016	Instrumental variables	Cross-section
Raza et al.	2016	Instrumental variables	Cross-section

Galarraga et al	2010	Instrumental variables and two stage residual inclusion	Panel Data
Lu et al	2012	Instrumental variables and two stage residual inclusion	Cross-section
4. Regression discontinuity (N = 6)			
Hou and Chao	2011	Regression discontinuity	Administrative Data
Camacho and Conover	2013	Regression discontinuity	Administrative Data
Miller et al	2013	Regression discontinuity	Cross-section
Bernal et al.	2014	Regression discontinuity	Cross-section
Sood et al	2014	Regression discontinuity	Repeated cross-section
Palmer	2015	Regression discontinuity	Cross-section
5. Combination (N = 19)			
Chen and Jin	2012	DID - PSM	Repeated cross-section
Fan et al	2012	DID - PSM	Repeated cross-section
Nguyen	2012	DID - PSM	Panel Data
Sparrow et al	2013	DID - PSM	Panel Data
Bai and Wu	2014	DID - PSM	Panel Data
Guindon	2014	DID - PSM	Panel Data
Cheng et al	2015	DID - PSM	Panel Data
Ghislandi, Manachotphong and Perego	2015	DID - PSM	Repeated cross-section
Yang and Wu	2015	DID - PSM	Panel Data
Yilma et al	2015	DID - PSM	Panel Data
Limwattananon et al	2015	DID and quintile regression	Repeated cross-section
Peng and Conley	2015	FE and IV	Panel Data
Dhillon et al	2012	FE with IV	Panel Data
Parmar et al	2012	FE with IV	Panel Data
Aji et al	2013	FE with IV	Panel Data
Liu and Zhao	2014	FE with IV	Panel Data
Jung and Streeter	2015	FE with IV	Panel Data
Aryeetey et al.	2016	FE with IV	Repeated cross-section
Rivera-Hernandez	2016	FE with IV	Panel Data
6. Other methods (N = 7)			
Atella, Brugiavini and Pace	2015	Finite Mixture Model	Repeated cross-section
Fenny et al	2015	Multinomial Logit	Cross-section
Liu, Wu, and Liu	2014	Structural equation modelling	Cross-section
Hou et al	2014	Two-part model	Repeated cross-section
Abrokwah et al	2014	Two-part model	Cross-section
Pfutze	2014	Weighted Exogenous Sampling Max Likelihood	Cross-section
Pfutze	2014	Weighted Exogenous Sampling Max Likelihood	Repeated cross-section

## **Section 6.4 Methods for controlling selection on observables**

### **6.4.1 Linear regression**

The linear regression model can produce estimates that can have a causal interpretation if the treatment variable is randomly assigned (Angrist and Pischke, 2008). In observational data, it is also possible to obtain a causal effect if the selection into treatment is based only on observable factors (Jones and Rice, 2011). The core assumption of this approach is that while the selection into treatment is not randomly assigned, it should be assumed that the selection happens independently from the outcome of the interest conditional on observable factors. More specifically, whilst conditional on the observable factors, the selection into treatment should be independent of the counterfactual outcome, which is defined as the outcome for a group had it been assigned to a different group. This is often called the conditional independence assumption (CIA). Coupled with the additional assumption that the conditional mean of the counterfactual outcome is a linear function of the observable factors, the standard linear regression model becomes the simplest method to estimate the average treatment effect on the treated (ATT) (Jones and Rice, 2011). When applied to health care, this linearity assumption is found to be too restrictive due to many of the outcome variables being of a binary variable nature. Even when the outcome variable is a continuous variable, it often features as a non-normal, skewed distribution, as in the case of health expenditure data and number of doctor visits. While it is possible to transform the data, the resulting estimate does not come with the original scale which then needs to be rescaled into its original value. This is complicated by the difference of error term distribution between the original and scaled variables (Duan, 1983). To avoid this retransformation problem, it is recommended that an alternative method is used, such as the generalised linear model (GLM) with quasi-likelihood estimation or propensity score matching (PSM). In the next sub-section, I will further consider the role of PSM as an alternative non-linear approach to dealing with non-normally distributed variables.

## 6.4.2 Propensity score matching (PSM)

Matching can solve the selection on the observable problem by ensuring that the control groups have similar observable characteristics, except for the different treatment, with the treated group. Exact matching, in which individuals are paired directly on key variables of interest, is possible when the number of matched variables are not too many. Adding more matching variables can increase the precision of exact matching, but it also increases the possibility of excluding patients who do not match, further reducing sample size and the variability of the patient population (Stuart, 2010). Propensity score matching is a technique that matches the control and treated groups on the basis of their propensity score, the probability of receiving treatment. Propensity score matching can help to reduce the dimensionality problem of the general matching technique if a high number of variables needs to be controlled (Caliendo and Kopeinig, 2008). In the context of this thesis, the propensity score for being insured can be constructed as a function of observable confounding factors using non-linear models, such as probit or logit. Thus, insured individuals will be matched with the control individuals who have a similar propensity score or are within the acceptable range of scoring.

PSM is also often used as an alternative to standard regression analysis in the presence of a transformed outcome variable. It is also more straightforward to perform a robustness check of PSM compared with regression adjustment. Finally, PSM has more intuitive appeal in relation to creating groups of similar treatment and control, ultimately making it easier to produce an explanation for non-technical people (Zanutto, 2006).

In order to derive a treatment effect from the PSM method, there are two important assumptions that need to be justified. Firstly, this method relies on the conditional independence assumption (CIA) in which the potential outcomes are independent of the treatment status, conditional on the observed characteristics (Heinrich, Maffioli and Vázquez, 2010). It means that the counterfactual effect for the treated can be inferred, as in the case of the randomised trial, so that the observed change in



outcome between the treated and the control groups can be attributed to the effect of the programme. The second assumption is the overlap assumption, in which the individuals have a chance of being selected for either the treated or control groups; there is no individual who is impossible to be in any group (Heinrich et al., 2010). If under selected observable characteristics, an individual can only be in one group and not in another, this assumption can fail. Both assumptions are needed to identify the Average Treatment Effect (ATE). It is possible to use a weaker version of both assumptions, but this will only allow us to identify the Average Treatment on Treated (ATT). Under the weaker assumptions, the mean of the distribution of the potential outcome is independent of the treatment status, and only treated individuals are required to have a chance to be selected into either the treated or control groups (Faria et al., 2015). The latter implies that it is possible to select control groups from a different area in which the treatment is applied, as long as they have similar observable characteristics with the treated group.

In the application of PSM in an empirical study, Dehejia and Wahba (2002) identify three issues: the decision to match with or without replacement, the number of control units to be matched with the treated units, and the matching algorithm. For the first issue, the decision depends on the balance between reducing bias and increasing efficiency. Matching with replacement can reduce bias by ensuring that the matched control group has a similar or close propensity score with the treated group, but this may decrease efficiency since the matched controls are no longer independent. Meanwhile, matching without replacement may increase our precision by ensuring independence among matched controls, but it may also increase bias in terms of the low-quality of the match between the treated and control units.

In deciding on the number of matches, the trade-off between bias and efficiency should also be considered. By choosing one single unit, we can reduce the bias, but choosing multiple units may increase our precision of the estimates. The next step is choosing the matching algorithm. The simplest method is nearest neighbour matching with a ratio of 1:1, which means that each individual in the treated group will be matched with an individual from the control group who has the smallest

distance of propensity score from the treated individual. However, this method can create a bad match if the closest neighbour is too far away. We can impose an acceptable range (caliper) on the propensity score for a control group that is allowed to be selected as a match; this method is called caliper matching. It implies that an individual from the control group is chosen as a matching partner for a treated individual who lies within the caliper and is closest in terms of the propensity score, but the decision regarding what distance is appropriate is somewhat arbitrary (Caliendo, 2005). Another alternative method is kernel matching, in which a non-parametric method is employed to determine the weighted average of the outcomes of all of the untreated individuals, which would then be compared with the treated individuals. Propensity score can also be used to create intervals and we can ensure the same propensity score on average between the treated and control groups.

One final note should be made about the selection of variables to create a propensity score. We should ensure that the selected variables are unaffected by the treatment status because failing to do so will cause the CIA assumption to fail. It is best to include variables that are collected before the treatment begins. Also, the instrumental variable should not be included as it will increase the bias in the treatment effect estimate (Wooldridge, 2010).

In application, the CIA assumption is an untestable assumption. We should therefore justify our analysis with reference to the expert literature. The most common check in empirical work is the overlap assumption and this needs to be assessed thoroughly despite the choice of matching algorithm.

Based on the preceding review, it has been shown that PSM is one of the most common methods used to estimate the causal effects of a health insurance programme on utilisation and financial protection, whether in combination with another technique or on its own. The common support assumption is often reported properly. From eight studies using PSM as their main estimation method, only two studies perform sensitivity analysis in terms of the different choices of the matching algorithms (Alkenbrack and Lindelow, 2015; Makhloufi et al., 2015). Moreover, there

are three studies which do not discuss important the assumptions made to justify the validity of the propensity score (Avilla-Burgos et al., 2013; Blanchet et al., 2012; Robyn et al., 2012). Overall, these eight studies are judged to have a high risk of bias because PSM is unable to control for unobserved confounding factors. High-quality papers tend to combine PSM with another method that is capable of controlling for unobserved factors, such as PSM and DID or PSM and IV (Cheng et al., 2015; Nguyen, 2012; Lu et al., 2012;).

## **Section 6.5 Methods for controlling selection on unobservables**

### **6.5.1 Instrumental variables (IV)**

The idea behind IV estimation is to find a variable (also commonly called an “instrument”) which is correlated with the treatment but only within the outcome through its effect on the treatment. This is known as the exclusion restriction or instrument exogeneity, as the IV is excluded from the original model and restricted to appearing in the treatment choice equation only. The variation in the instrument is then utilised to identify the causal treatment effect. Intuitively, since the instrument is a source of variation correlated with the treatment decision, it gives some exogenous variation to approximate randomisation (Faria et al., 2015). However, this assumption cannot be tested in a simple IV estimator; it must be justified based on knowledge from the literature or expert opinion. Nevertheless, when we have more than one instrument per endogenous variable, it is possible to test whether some of the instruments are uncorrelated within the structural error term. The procedure of comparing different IV estimates of the same parameter is called the over-identifying restrictions test (Wooldridge, 2013).

The second assumption is called instrument relevance, which means that the instruments have to be correlated, positively or negatively, with the endogenous explanatory variable (Wooldridge, 2013). Unlike the first assumption, the second one can be tested easily. An instrument with low correlation between the endogenous regressors is called a weak instrument. In this case, the model is said to be weakly

identified, leading to a loss of precision in the estimate of the treatment effect. Consequently, the usual statistical inference, based on t-statistics and the standard normal distribution, could be misleading. There is some evidence that IV estimation with weak instruments may perform badly and even more poorly than OLS (Imbens and Wooldridge, 2009). The asymptotic bias in the IV estimator is less than that for OLS, only if the ratio of correlation between the instrument and the endogenous variable is less than the correlation between the endogenous variable and the error term of the original model (Wooldridge, 2013).

For a model with an endogenous variable, the standard first-stage F-statistic can be used to test for identifying a weak instrument, in which weakness is identified in terms of the size of the bias of the IV estimator relative to that of the OLS estimator. For multiple endogenous variables, one should use the Cragg-Donald statistic method to evaluate the overall strength of the instruments (Stock and Yogo, 2005).

Another key assumption in standard IV estimation is that the treatment effect is homogeneous (the treatment effects are the same for everybody in the population). Alternatively, the treatment effect can be assumed to be heterogeneous but requires the assumption that selection into treatment is not influenced by the unobserved heterogeneity (individual specific effect) in the outcome (Faria *et al.*, 2015).

Despite the difficulty of finding a good instrument, IV is one of the most common methods used to estimate the impact of health insurance in developing countries. There are 12 studies that utilise IV as the main method to determine a causal effect of health insurance. Some of the common instruments are:

1. Randomisation of eligibility: true randomisation (Fink *et al.*, 2013; Parmar *et al.*, 2012) or a natural experiment on the gradual roll out of the insurance (Wirtz *et al.*, 2012; Galarraga *et al.*, 2010)
2. The community rate of enrolment in which the denominator is the number of eligible households in a particular area minus the observed households

(Cheung and Padieu, 2013; Nguyen, 2012; Lu et al., 2012; Lu, Liu and Shen, 2012; Trujillo et al., 2010)

3. Eligibility for other government social protection (Aji *et al.*, 2013)
4. Drinking behaviour as a proxy for risk attitude (Chen *et al.*, 2014)
5. Lagged dependent variable (Dhillon *et al.*, 2012)
6. Self-employment status (Trujillo *et al.*, 2010)
7. Participation in a community meeting or community organization (Aji *et al.*, 2013)
8. The type of housing area per household member as the instrument for health spending (Lu, Liu, and Shen, 2012; Lu *et al.*, 2012)
9. Simulated eligibility score to instrument the “real” yet manipulated eligibility score (Miller *et al.*, 2013)

The two important assumptions are often justified in the study, but there is no discussion about the tests in the results sections. However, this could be partly explained by the word count limitation imposed by the journals so that the authors must select the most important tables to be displayed in their paper. Stronger IV studies tend to either combine their method with other strategies, such as fixed effect (Liu and Zhao, 2014; Dhillon et al., 2012; Parmar et al., 2012) and PSM (Lu *et al.*, 2012; Lu, Liu, and Shen, 2012; Wirtz *et al.*, 2012). Furthermore, Fink *et al.* (2013) used the insurance rollout assignment, which was a random assignment from 33 available districts, as an instrument for insurance enrolment. In addition, bivariate probit is also used as an alternative to the IV method when the outcome variables are also binary variables, such as in the probability of incurring catastrophic health expenditure (Galarraga *et al.*, 2010) or the probability of using outpatient/inpatient care (Chen *et al.*, 2014).

## 6.5.2 Panel data methods

Panel data offers the advantage of using the individual as their own control since each individual is observed at different time periods. The assumption that is required to be able to identify a treatment effect is that the individual's unobserved heterogeneity in the outcome model is time invariant. There are two separate models, depending on which approach is taken to eliminate the unobserved term. If the individual's unobserved effect is suspected to be correlated with the covariates in the model (including treatment), a fixed effects model or a first difference model can be used. These models do not use the cross-sectional variation across individuals and might, therefore, be less efficient than the random effects estimator (Wooldridge, 2013). Alternatively, if it is assumed that the individual's unobserved effect is random, and thus not correlated with covariates in the model, a random model should be used. This estimator, however, assumes that the unobserved determinants of heterogeneity in the outcomes do not have an effect on selection. The Hausman test of fixed versus random effects is routinely reported by standard software when using these models. It is worth noting that rejection of the null hypothesis of this test could also be due to a misspecification of the model (Cameron and Trivedi, 2005).

There are not many papers that utilise panel data because this type of data collection requires more effort and takes a longer period of time. In the context of a developing country, due to resource constraints, the data collection process is completed over a longer period of time, but the authority often demands quicker results to evaluate the policy.

## Section 6.6 Natural experiment

Natural experiment approaches make use of exogenous events. Exogenous events are those that produce a random assignment of individuals to treatment or to eligibility for treatment.

### 6.6.1 Difference-in-difference (DID)

DID has been used widely in many policy evaluations (Angrist and Pischke, 2009). DID compares the changes in outcomes over time between a population that is enrolled in a programme (the treatment group) and a population that is not (the comparison group). The difference in the before-and-after outcomes for the treatment group – the first difference – controls for confounders that are constant over time in that group, since we are comparing the same group to itself. The second difference involves measuring the before-and-after change in outcomes for a group that did not enrol in the programme but was exposed to the same set of environmental conditions to capture time-varying confounders. By subtracting the second difference from the first difference, we will be able to eliminate the selection bias between those who choose to enrol and those who choose not to enrol to produce a better estimate of the counterfactual (Gertler et al., 2011).

The difference in difference estimator is defined as the difference in average outcome of the treatment group before and after treatment, minus the difference in average outcome in the control group before and after treatment (Lechner, 2011). To identify a treatment effect, this method uses either longitudinal data for the same individuals or repeated cross-sections drawn from the same population, before and after the treatment. By comparing the changes over time in the means of the treatment and control groups, the DID estimator allows for both group-specific and time-specific effects. In general, the DID approach will identify the ATT (Faria et al., 2015).

One of the most common problems with the difference in difference estimates is the failure of the parallel trend assumption which assumes common trends across the treatment and control groups (Imbens and Wooldridge, 2009). If outcome trends are different for the treatment and control groups, then the estimated treatment effect obtained by difference-in-difference methods would be biased. The reason is that the trend for the control group is not a valid estimate of the counterfactual trend that would have been observed for the treatment group in the absence of the treatment. A good validity check is to compare changes in outcomes for the treatment and

comparison groups before the programme is implemented (Gertler et al., 2011). One way to solve this problem is to obtain more data on other time periods before and after treatment to see if there are any other pre-existing differences in trends. To check for equality of pre-intervention trends, we need at least two serial observations on the treatment and comparison groups before the start of the programme. It may also be possible to find other control groups which will provide additional underlying trends. If both the original and additional groups are valid control groups, we would find that the estimated impact is approximately the same in both calculations.

Another way to test the assumption of equal trends would be to perform what is known as a “placebo” test. For this test, it is necessary to conduct an additional difference-in-differences estimation using a group that was not affected by the treatment as the “fake” treatment group. If we perform DID estimation between the “fake” treatment group and the control group, we should find no impact at all. Otherwise, there must be some underlying trend between those two which would also cast doubt on the assumption of a parallel trend between our original treatment group and the control group (Gertler et al., 2011)

When using repeated cross-sections of individuals instead of longitudinal data, we also need to add one more assumption in addition to common trend assumptions. There should be no systematic changes in the composition of the groups so that the average individual fixed effect can be eliminated (Lechner, 2011).

Difference-in-difference has become more popular in an evaluation study of the impact of health insurance in developing countries due to its flexible design in either repeated cross sectional or longitudinal data. However, only a few good studies have justified the parallel trend assumptions which may cast doubt on the validity of the reported causal effect. In addition, it is increasingly common to combine DID and PSM to tackle selection bias on both observable and unobservable characteristics (Cheng et al., 2015; Yang and Wu, 2015; Guindon, 2014; Sparrow, Suryahadi and Widyanti, 2013; Chen and Jin, 2012; Nguyen, 2012).



## 6.6.2 Regression discontinuity (RD)

The basic idea behind the RD design is that assignment to the treatment is determined by the value of a predictor, or the forcing variable, being on either side of a common threshold. The RD estimator uses the discontinuity to identify a treatment effect by assuming that the individuals on different sides of the discontinuity are the same in terms of the unobservable that affects the outcome, and that treatment differs simply because of the discontinuity in the eligibility rule (Imbens and Wooldridge, 2009). The design often arises from government decisions whereby the decision for individuals to participate in a programme is restricted by budgetary constraints and is determined by clear transparent rules, not an indiscretion.

There are two general settings for RD design: sharp and fuzzy. In the sharp design, the treatment assignment is a deterministic function of the forcing variable, for example, when all individuals above a certain income threshold are treated but those below the threshold are not. Alternatively, in the fuzzy design the probability of treatment need not change from zero to one at the threshold; it only requires a discontinuity in the probability of assignment to treatment at the threshold, for example, if other variables (including unobserved variables) apart from income determine treatment. In this case, treated as well as untreated individuals are found on both sides of the threshold. Both designs depend on the assumption that the conditional mean of the outcome functions for the treated and control groups are continuous at the discontinuity point (Faria et al., 2015).

After applying the RD design, we should perform two specification checks. Firstly, we may look for discontinuities in the average value of the covariates around the threshold. Finding a discontinuity in other covariates typically casts doubt on the assumptions underlying the RD design (Imbens and Wooldridge, 2009). Secondly, to check the possibility of manipulation by the individuals, we should check the density of the covariate that underlies the assignment at the threshold (McCrary, 2008). A jump in the density at the threshold is probably the most direct evidence of some

degree of sorting around the threshold, and should provoke serious scepticism about the appropriateness of the RD design (Lee and Lemieux, 2010).

Because the RD design estimates the impact of the treatment around the threshold, we can only estimate the Local Average Treatment Effect or LATE (Gertler et al., 2011). Consequently, the estimate cannot be generalised to observations further away from the threshold where eligible and ineligible individuals may not be as similar. It also raises challenges in terms of the statistical power of the analysis. Since effects are estimated only around the threshold, fewer observations can be used than in other methods that would include all observations. Relatively large evaluation samples are required to obtain sufficient statistical power when applying RD design. According to Table 6-1, there are six papers that utilised RD design to evaluate the impact of health insurance programmes in developing countries (Palmer et al., 2015; Bernal, Carpio and Klein, 2014; Sood et al., 2014; Camacho and Conover, 2013; Miller, Pinto and Vera-Hernandez, 2013; Hou and Chao, 2011). All of them are considered to be high quality with a low risk of selection bias, based on the quality assessment done in Chapter 5. The similarity among them is the ability to gather data necessary to determine the threshold, which may prove quite challenging in the Indonesian context. This will be discussed in the next section.

## **Section 6.7 Applicable methods**

Following the description above of potential methods, there are several methods that could be used for my empirical study. The method that is chosen needs to account for both observable and unobservable factors that influence health insurance status. The first possible method is the instrumental variable, but it is moderately difficult to obtain a strong instrument. I attempted to use several potential instruments, such as the local JKN advertisement effort by the local government, participation in community organisation, and individual risk preference, but all of them are proven to be weak instruments based on the first-stage F-statistic. Weak instruments may introduce more bias than OLS estimation (Wooldridge, 2014). Furthermore, most of

my outcome variables are non-normally distributed which complicates the weak instrument testing.

Another possible method is regression discontinuity as this method most closely resembles true randomization allocation. However, RD design has been proven to be challenging to implement in Indonesia. Most poverty alleviation programmes, including the JKN programme, are targeted based on a proxy means-testing technique with 14 indicators including housing characteristics, frequency of food consumption, educational and occupational levels of household heads, and asset possession. In 2010, the central government updated the database of 40% poorest population to be used for poverty alleviation programs, including public health insurance. However, the local governments were still able to modify the list based on their own criteria. This was confirmed from my visit to BPS (Badan Pusat Statistik/Indonesian Statistics) in Jakarta. Thus, it is quite difficult to reproduce the list in order to justify a regression discontinuity (RD) analysis. One paper has tried to evaluate the unconditional cash transfer programme in Indonesia and they report that it is almost impossible to reconstruct the proxy means test scores, even to justify fuzzy RD (Bazzi, Sumarto and Suryahadi, 2012).

An alternative and feasible method is to combine propensity score matching and the difference in difference method which has been used to estimate the causal effect of health insurance in several developing countries (Yang and Wu, 2015; Cheng et al., 2015; Guindon, 2014; Sparrow, Suryahadi and Widyanti, 2013; Chen and Jin, 2012; Nguyen, 2012). There is also an increasing trend towards employing DID in combination with PSM (10 studies). There are several reasons for combining PSM and DID. Firstly, PSM and DID allow the researcher to control both observable and unobservable selection bias (Cheng et al., 2015; Yang and Wu, 2015; Guindon, 2014; Nguyen, 2012). Secondly, PSM does not impose any functional form on outcome variables (Sparrow et al., 2013). Thirdly, PSM and DID avoids the unobserved selection of insurance take-up by comparing the populations in the targeted and non-targeted areas, regardless of the actual household decision (Chen and Jin, 2012). Fourthly, the time trend assumption could be tested by conducting a falsification test:

defining treatment and the control group for both before and after the treatment, based on the information available after the treatment (Cheng et al., 2015)

Considering the availability of panel data from the IFLS dataset, with its rich information about individuals and household characteristics, and the method's flexibility in terms of handling non-normally distributed variables, I decided to use a combination of PSM and DID as my primary method for estimating the impact of the JKN programme. The next three chapters will present the empirical findings of the effects of the JKN programme on access to care (Chapter 7), financial protection (Chapter 8) and health status (Chapter 9).

# Chapter 7 The JKN programme and its impact on access to care

## Section 7.1 Introduction

In the previous chapters, it has been suggested that health insurance can be effective in increasing access to care, usually measured in terms of utilisation of formal care facilities, but that the evidence is mixed. In chapter 4, I found several systematic reviews that favour the positive effect of health insurance in improving access to health care services (Comfort et al., 2013; Giedion et al., 2013; Spaan et al., 2012; Ekman, 2004). In chapter 5, I updated the systematic review by searching for more recent evidence from 2012 to 2016 and found that 30 out of 38 studies reported the positive effect of health insurance in increasing utilisation of curative care.

Restricting the evidence by choosing studies with stronger methodological techniques revealed that seven studies found a positive effect (Levine, Polimeni and Ramage, 2016; Palmer et al., 2015; Bernal, Carpio and Klein, 2014; Miller, Pinto and Vera-Hernandez, 2013; Nguyen, 2012; Yilma, Van Kempen and De Hoop, 2012; Hou and Chao, 2011), one study found no statistically significant effect (Raza et al., 2016), and one study found negative effect on utilisation (Sheth, 2014). In this chapter, I examine whether the implementation of Indonesia's JKN programme has improved access to health care for its enrollees. The specific objectives are:

- a. To evaluate whether the JKN programme has, on average, increased the probability of utilisation for both outpatient and inpatient care;
- b. To evaluate whether the JKN programme has, on average, increased the frequency of utilisation for both outpatient and inpatient care; and,
- c. To assess the heterogeneity of the JKN programme effect in relation to living in an urban or rural area, socioeconomic status and the availability of health care facilities in the area.

In my effort to estimate the treatment effect of the JKN programme, I need to control for self-selection bias in the insurance status; individuals who expect to consume more medical treatment are more likely to purchase health insurance (Waters, 1999). To address this in estimating the effect of the JKN programme on access to care, the

combination of propensity score matching and difference-in-difference was chosen based on the methodological review in chapter 6. In this chapter (and the next two chapters), the data come from the Indonesian Family Life Survey (IFLS), a longitudinal survey in Indonesia that follows the same cohort over time from 2007 to 2014.

## Section 7.2 Conceptual framework of access to health care

A number of frameworks have been proposed in the literature to define access to health care. Andersen (1968) first provided a simple framework to model families' use of health services in the USA (see Figure 7-1) and this model has been used extensively in studies which investigate the use of health services (Babitsch, Gohl and von Lengerke, 2012; Titaley, Dibley and Roberts, 2010; Chakraborty et al., 2003; Becker et al., 1993). Andersen suggests that use of health services is the consequence of need, whilst the need itself is influenced by two main factors: predisposing characteristics and enabling resources.

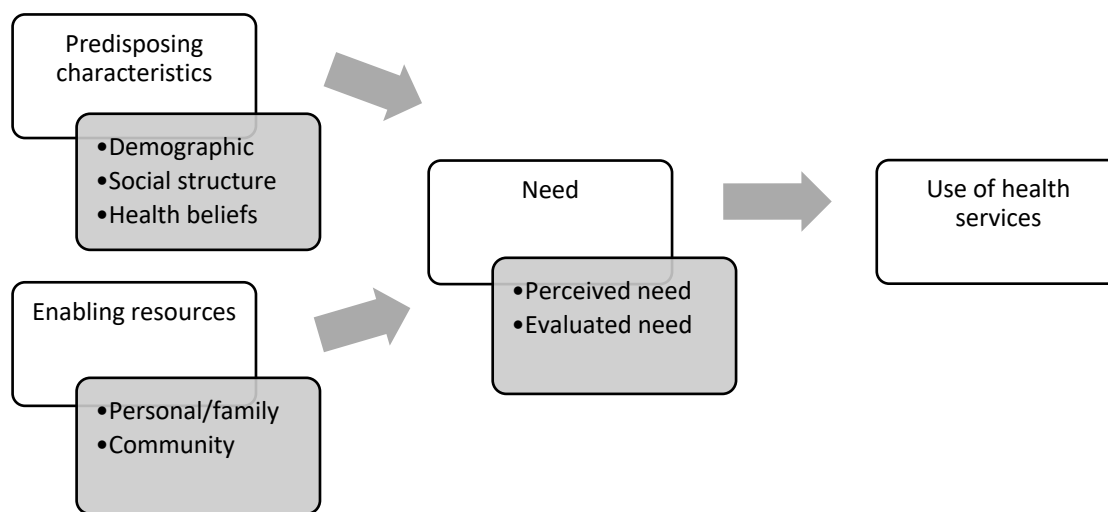


Figure 7-1 Andersen's behavioural model of access to care, early version (Andersen, 1968).

Predisposing characteristics can be understood as the innate factors within an individual and these are relatively unchangeable. There are three different categories of predisposing characteristics: demographic, social structure and health beliefs.

1. Demographic represents the biological factors that drive people to use health services, such as age and gender. Children may demand more use of health services, for example, immunisation, whereas older people are more likely to suffer from chronic diseases which result in a higher need for regular visits to the general practitioner (Collins and Klein, 1980).
2. Social structure represents the social status and the ability of an individual to cope with any given problem. Social status can be measured by occupation, education and ethnicity, while culture and social networks may contribute to coping mechanisms (Andersen, 1995).
3. Health beliefs represent people's values and knowledge which are reflected in their attitudes towards the need for health services. Institutional trust towards modern health care facilities can influence a patient's beliefs about health (Mohseni and Lindstrom, 2007). Furthermore, trust facilitates communication and patient disclosure which encourages people to utilise health services (Gilson, 2003). Health beliefs also include cultural norms and prevailing political perspectives on how health services should be organised and financed (Andersen and Davidson, 2007).

Enabling resources must be present in order for the use of health services to be realised. Enabling resources can be divided into two factors: personal/family and community. Income or health insurance acts as a personal factor that supports the fulfilment of health care utilisation (Andersen, 1968). Virtually all supply-side factors, such as the availability of adequate health facilities in the nearby area and a good medicine procurement system, are included in the community factor. The means of transportation to reach the health facilities (Arcury et al., 2005) and reasonable waiting times (Gulliford et al., 2002) are also considered to be enabling factors in health service use.

Both predisposing characteristics and enabling factors can contribute to the presence of perceived need that reflects the role of social aspects explaining an individual's care-seeking behaviour (Andersen, 1995). Based on perceived need, an individual may decide to seek help from the health care professionals who have the capacity to

evaluate the need for medical treatment. This evaluated need reflects more of the medical aspects of access to health care and it is easily observed in the data, for example by looking at the reported number of acute or chronic medical conditions from patients. While perceived need can explain individual care-seeking behaviour and adherence to a medical treatment, evaluated need will be more closely related to the type and amount of treatment that will be provided after an individual has consulted with a medical care provider.

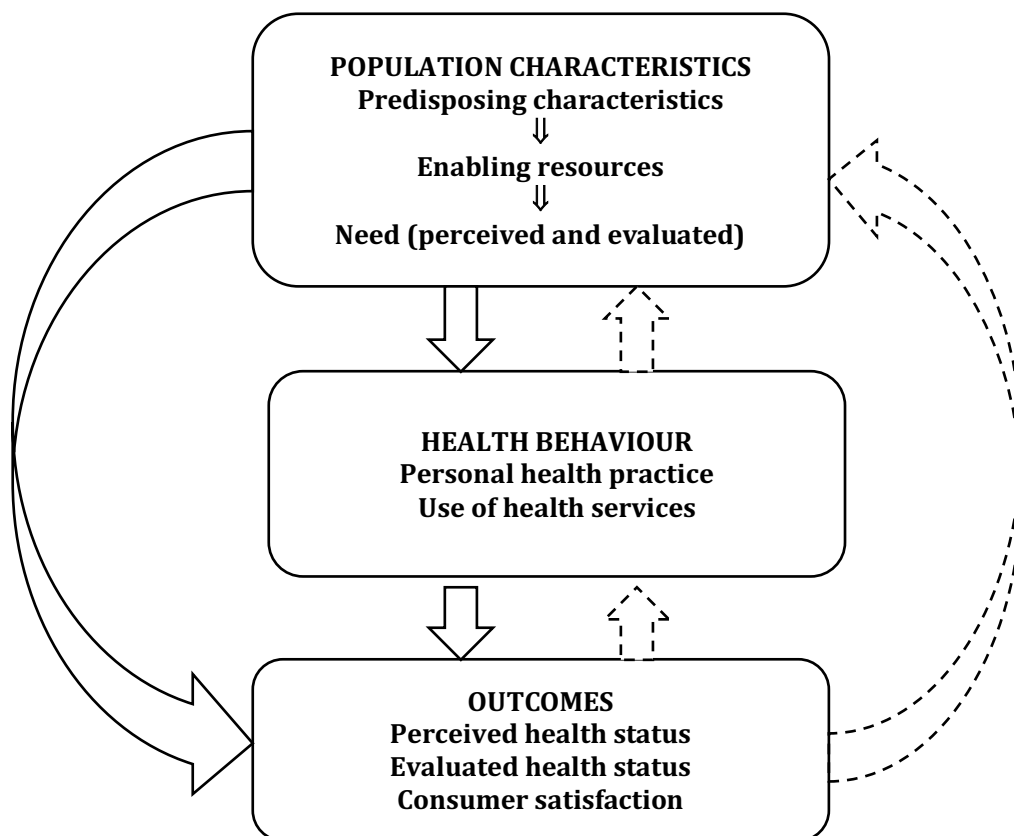


Figure 7-2 The behavioural framework of access to care (a more recent model)

In its more recent model (see Figure 7-2), Andersen includes more factors that contribute to the realisation of access to health care. Firstly, he distinguishes between two types of access: potential access which reflects the presence of enabling resources and realised access representing the actual use of services. He further introduces the role of a health care system and external conditions (physical, political, economic) as environmental factors which influence the presence of population characteristics. Next, the use of health services is perceived as an



individual's behaviour to promote his/her health outcomes. Another health behaviour aspect is personal health practice, such as diet, exercise and self-care, which acts as a complementary factor in the utilisation of formal health services to influence health outcomes.

Andersen includes health outcomes as a feedback loop affecting the predisposing characteristics of perceived need and health behaviour. Health status is often evaluated by medical professionals and it offers a more objective measure rather than health status perceived by patients. However, perceived health status may play an important factor in explaining a patient's decision to seek care. Andersen also considers consumer satisfaction as another important outcome which complements both perceived and evaluated health status. The inclusion of these three outcomes implies that the health outcomes after the first use of health services may reinforce the subsequent use of health services in the future. If an individual has been diagnosed with a chronic illness (for example, diabetes or hypertension), this illness may alter his/her attitude to his/her condition that previously might not have been perceived as a serious complaint.

Andersen's model provides a simple and applicable model to evaluate the treatment effect of policies which aim to improve access to health care while controlling for other factors that may influence the actual use of care. In this model, health insurance can be seen as an enabling factor that reinforces the patient's decision to use formal care. I focus on the use of formal health care because traditional care is not covered by the JKN programme. Control variables may include predisposing characteristics (for example, age and gender, urban/rural location, educational status and socioeconomic status), enabling factors (for example, the availability of health services) and health outcomes. One issue with this model is the inclusion of health outcomes as a control variable which may pose a reverse causality problem in a regression model of utilisation as the dependent variable. The inclusion of past health status may be included in the model instead, assuming future use of care does not influence the previous health outcome, which is quite a reasonable assumption to be made.

## **Section 7.3 Methodology**

### **7.3.1 Survey methodology**

The main data were obtained from the Indonesia Family Life Survey (IFLS) waves 4 (2007) and 5 (2014). The IFLS is a national longitudinal survey of socioeconomic characteristics and population health; the survey is based on a sample of households living in 13 of the country's 27 Provinces, identified in 1993. Although only half of the provinces were chosen, those 13 provinces represented 83 percent of the Indonesian population. The selected provinces were chosen to maximise the representativeness of the population and for cost effectiveness reasons, given the vast area and difficult terrain of the country (Strauss, Witoelar and Sikoki, 2016). The IFLS is designed to provide data for studying behaviours and outcomes. The survey contains a wealth of information collected at individual and household levels, including multiple indicators on economic and non-economic well-being: consumption, assets, education, migration, labour market outcomes, marriage, fertility, contraceptive use, health status, use of health care and health insurance, relationships among co-resident and non-resident family members, processes underlying household decision-making, transfers among family members and participation in community activities.

The main sample in this study consists of adult respondents who completed individual questionnaires in both the 2007 and 2014 IFLS surveys. The JKN programme began in January 2014 and was implemented nationally. IFLS 2014 was conducted in September 2014, which means that IFLS 2007 data can be treated as the baseline and 2014 data as the follow-up, thereby allowing for panel data analysis. There were 29,014 individuals who completed individual questionnaires in 2007, but only 22,711 individuals completed the same questionnaires in 2014, yielding an attrition rate of 21.73%. The reasons for non-completion among the 6,303 individuals are depicted in Figure 7-4.

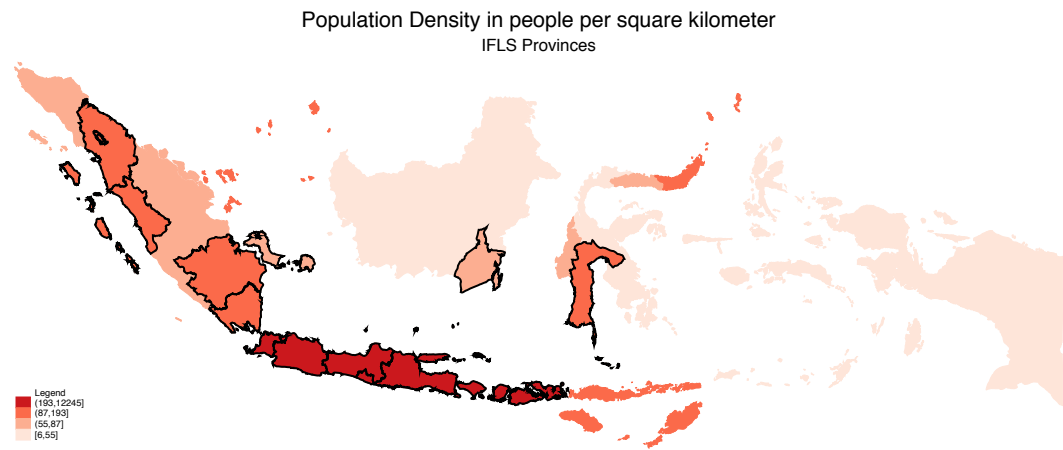


Figure 7-3 Map of Indonesia showing IFLS provinces and population density

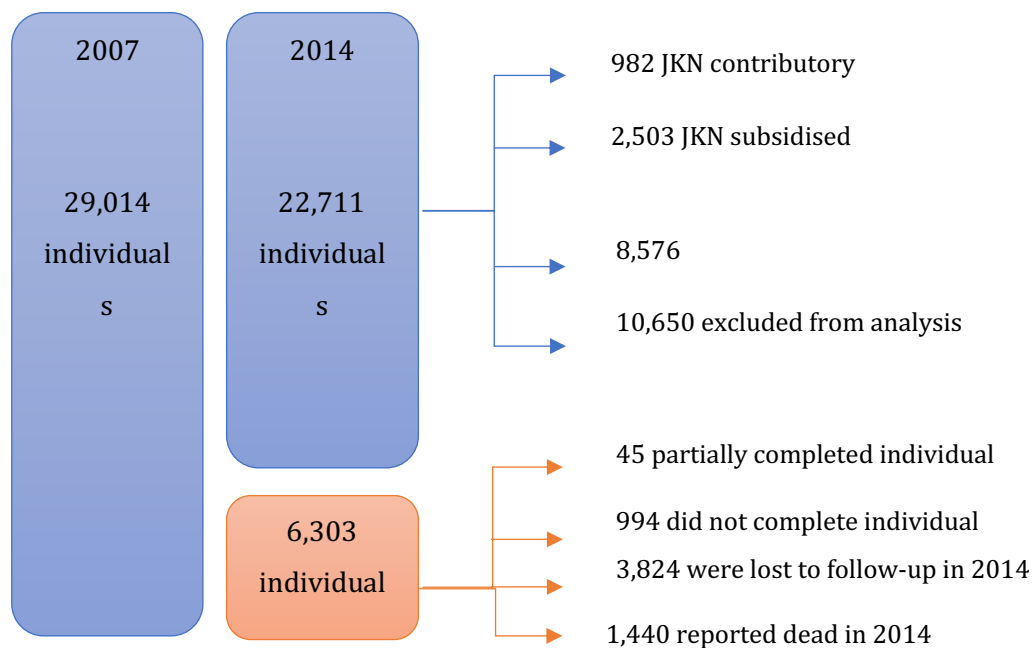


Figure 7-4 Summary of main sample from IFLS 2007 and 2014

### 7.3.2 Treatment variables

In order to estimate a causal effect from a before and after study, it is important to ensure that both the treated and control groups have similar characteristics in the baseline. In the context of health insurance evaluation, this means that both groups must be uninsured in 2007. Furthermore, to limit the spillover effect from other types of health insurance, the treatment group must have no other type of insurance

other than the JKN programme. Figure 7-4 provides the summary of the main sample in this analysis. Out of the 22,711 individuals who were followed from 2007 to 2014, 10,650 individuals were excluded from this analysis for two reasons: firstly, they were uninsured in 2007 but insured through non-JKN insurance in 2014; and secondly, they were insured by any type of insurance in 2007, regardless of their insurance status in 2014.

As previously explained in Chapter 3, the JKN programme targets many different groups depending on their ability to pay and employment status. Some JKN enrollees were previously insured by ASKES (for civil servants), JAMSOSTEK (for formal sector employees), or private insurance (through their employers or a private decision). Following the baseline criteria of being uninsured, the above three groups were therefore excluded. Thus, the following treatment and control groups were defined for this analysis:

- (1) **JKN contributory group:** individuals who were uninsured in 2007 but then enrolled voluntarily in 2014 – there is potential for self-selection because individuals who expect to gain more health benefits are more likely to purchase health insurance. This group may represent self-employed individuals or people who work in the informal sector that are not categorised as poor.
- (2) **JKN subsidised group:** individuals who were uninsured in 2007 but qualified for subsidised JKN premiums in 2014 due to their socioeconomic status. This group is qualified for subsidised premiums based on a proxy means test defined by the government.
- (3) **Uninsured group:** individuals who were uninsured in 2007 and remained uninsured in 2014.

Both the contributory and subsidised groups received almost similar medical benefits from the JKN programme but the contributory group could choose to pay a higher premium in exchange for better non-medical hospital services. To eliminate the

spillover effect from other health insurance, individuals who reported having more than one health insurance membership, including private insurance, were excluded. Based on this classification, my analysis included 12,061 individuals of which 982 individuals were in the contributory group, 2,503 were in the subsidised group, and 8,576 were still uninsured in 2014.

### **7.3.3 Outcome and control variables**

IFLS data provides two types of utilisation information: outpatient and inpatient care. For both outpatient and inpatient, two types of utilisation data were recorded: the probability of visits and the unconditional number of visits. These two datasets were aggregated into three groups based on type of health facility: public and private. All utilisation data were recorded between September 2014 – March 2015, at least 8 months after the introduction of the JKN programme on 1 January 2014. Outpatient data were recorded based on four weeks period prior to the survey and inpatient data were based on twelve months period. It might be an issue if the inpatient visit happened before 1 January 2014. Fortunately, IFLS data provided information on the time of survey allowing me to split the sample between observations made in 2014 and 2015 and establish whether the effects of the JKN programme are any different across the two groups. It will be shown in the robustness check sub-section.

The next step was to choose control variables that could be associated with the insurance decision and outcome variables (i.e. health care utilisation); and, if these were not included in the model, they would confound the causal relationship between the insurance and the outcome variables. Based on Andersen's model, it is necessary to include predisposing characteristics and enabling factors as control variables. To capture predisposing characteristics, I included gender, age, marital status, and locality of residence. Educational status and socioeconomic status are chosen to represent enabling factors.

Socioeconomic status is considered to be the most important enabling factor. While income and employment status have been the standard variables for measuring socioeconomic status in high-income countries, these two variables rely on the availability of rich dataset which may be hard to find in low-middle income countries. The asset index has been used as a proxy measure of living standards when neither income nor expenditure data are available (Moser and Felton, 2009; Booysen et al., 2008; Sahn and Stifel, 2003; Filmer and Pritchett, 2001). Compared with consumption expenditure (which may also be used as a proxy for socioeconomic status), an asset index may act as a more reliable predictor with less measurement error in several settings (for example, education [Filmer and Pritchett, 2001] and health [Sahn and Stifel, 2003]). Information on the asset index is based on data collected in the IFLS household questionnaire. The questionnaire includes questions about household possession of durable assets such as a refrigerator, television and electricity; and dwelling characteristics such as number of rooms, house size in square metres, flooring material, outer walls material, roof material, main drinking source, type of toilet, type of sewage drain and main energy source for cooking.

Principal components analysis (PCA) is employed in creating the asset index, and a similar method is used to create a wealth index in the Demographic Health Survey (DHS) (Vyas and Kumaranayake, 2006). PCA considers the variation within each input variable and selects the best model to explain the underlying structure of the data. Values generated by PCA will normally have mean zero and standard deviation close to one, therefore it allows negative numbers. The input variables should have internal consistency or a strong correlation among themselves to ensure that all of them measure the same thing. To determine this internal consistency, it is advisable to calculate the Cronbach's Alpha from all of the input variables (Bland and Altman, 2002). When it is used as a research tool for comparing groups, Alpha values of 0.7 to 0.8 are regarded as satisfactory (Bland and Altman, 1997). The Alpha for the assets index in this analysis is 0.78 which lies within this acceptable range.

Following Andersen's model, the use of health services is also influenced by both perceived need and evaluated need. Perceived need reflects the role of social aspects

in explaining an individual's care-seeking behaviour and it has been captured by both predisposing characteristics and enabling factors. Evaluated need reflects the medical condition that prompts the care seeking. In this study, I used three health variables: number of acute conditions, number of chronic conditions and the presence of physical disability.

To control for supply-side factors which act as an important aspect of enabling factors, I also included the availability of health care facilities in the community area as a density variable. Density variables were derived from the number of facilities divided by the village/township size in hectares (1 hectare = 10,000 m<sup>2</sup>), separated into primary care facilities for outpatient care and hospitals for inpatient care. Binary variables for each IFLS province are also included to capture unobserved time-fixed effect that may correlate with the demand and supply of care in the area (Gravelle et al., 2003). To capture the supply-side factor more reliably, it is desirable to include distance in km to the nearest health care facility. Even though IFLS provides such measure, only less than 50% of the observation has no missing data hence its exclusion from my analysis. Lastly, I also included dummy variables for each enumeration area to capture time-varied variables which are common within the same area (e.g. local policy change or local economic shock).

#### **7.3.4 Estimation model**

A key empirical problem that hinders our efforts to estimate the impact of health insurance is the correlation between insurance enrolment and demand for health care. Since both voluntary and subsidised schemes were not distributed randomly, any observed and unobserved factors influencing the participation decision can potentially introduce bias into our estimation model. To solve this problem, I utilised the panel structure of IFLS data by combining a difference-in-differences (DID) approach with propensity score matching (PSM). I accounted for potential bias due to observable factors (or simply observables) using PSM which matches the treated with the untreated based on observables. Next, I used DID to account for any unobservable factors (or simply unobservables) that may be associated with

insurance decision-making as well as utilisation (Wagstaff, 2010a). Below, I discuss the intuition of obtaining the treatment effect from the combination of these two approaches and I will discuss some important assumptions which ensure the validity of this analysis.

If we observe two sets of outcomes –  $y_{it}^P$ , the outcome among the JKN enrollees;  $y_{it}^{NP}$ , the outcome for the uninsured – we can assume:

Equation 7-1

$$y_{it}^P = f(X_{it}) + G_{it} + \theta_t^P + \varepsilon_{it}^P$$

where  $f(X_{it})$  is a function of observable variables,  $X_{it}$ ;  $G_{it}$  is the expected benefit from the JKN accruing to those received it;  $\theta_t^P$  is a time-specific unobservable common to all participants; and  $\varepsilon_{it}^P$  is an idiosyncratic error term. For the uninsured, we have:

Equation 7-2

$$y_{it}^{NP} = g(X_{it}) + \theta_t^{NP} + \varepsilon_{it}^{NP}$$

$G_{it}$  does not appear in this second equation because the benefits of the scheme are assumed to be gained by JKN enrollees only. This implies the non-existence of the spillover effect. The changes before and after the introduction of JKN (which I labelled 0 and 1, respectively) for each of these groups can be written as:

Equation 7-3

$$\Delta y_{it}^P = f(\Delta X_{it}) + G_{i1} + \Delta \theta_t^P + \Delta \varepsilon_{it}^P$$

Equation 7-4

$$\Delta y_{it}^{NP} = g(\Delta X_{it}) + \Delta \theta_t^{NP} + \Delta \varepsilon_{it}^{NP}$$

The expected difference between the changes among the insured (i.e. Equation 7-3) and the uninsured (i.e. Equation 7-4) is therefore equal to:

Equation 7-5

$$\begin{aligned} DD^{P,NP} &= E(\Delta y_{it}^P) - E(\Delta y_{it}^{NP}) \\ &= E(f(\Delta X_{it})) - E(g(\Delta X_{it})) + E(G_{i1}) + \Delta \theta_t^P - \Delta \theta_t^{NP} + E(\Delta \varepsilon_{it}^P) - E(\Delta \varepsilon_{it}^{NP}) \end{aligned}$$

The treatment effect of the JKN programme on its enrollees is reflected by the  $E(G_{it})$ .



### 7.3.5 Propensity score matching

The first difference in Equation 7-5, i.e.  $E(f(\Delta X_{it})) - E(g(\Delta X_{it}))$ , represents the differences of changes in outcomes due to the difference in observables. This first difference can be eliminated through matching each treated individual with one or more untreated individuals who are similar in terms of observable variables ( $X_{it}$ ). In the context of JKN, there are many control variables that may influence both the uptake of JKN insurance and health care utilisation, such as age, gender, socioeconomic status, dwelling area, education and health condition. Performing exact matching on too many variables leads to an insurmountable number of possible combinations, a condition called the “curse of dimensionality” (Dehejia and Wahba, 1999). To overcome this challenge, I matched the insured with the uninsured based on the conditional propensity score, defined as the probability of the uptake of the treatment conditional on all the covariates  $X$ . This method is called Propensity Score Matching [PSM] (Rosenbaum and Rubin, 1983). PSM works by summarising information given by the observable factors into a one-dimensional metric, the propensity score.

Another attractive feature of PSM compared with regression type estimators is its nonparametric nature because PSM assumes a flexible functional form to estimate the outcome model (Rosenbaum and Rubin, 1983). A better statistical balance between treatment and control group after matching based on the estimated propensity score is more important than finding the appropriate model for the outcome variables (Wagstaff, 2010a). To ensure the validity of the estimated treatment effect, it is important to ensure the exogeneity of the observables in estimating the propensity score by choosing pre-treatment characteristics (Caliendo and Kopeinig, 2008).

To implement PSM, a logit model was estimated for the log-odds of enrolment in the JKN programme in 2014 using control variables in 2007. Based on this model, the propensity score was predicted for each individual for both voluntary and subsidised groups separately. The use of covariates from 2007, instead of 2014, was chosen to

ensure the exogeneity of the observables. In this application, the model is not a behavioural one, but simply a statistical device that enables me to weight the differences in observable variables between the treated and untreated groups (Imbens and Rubin, 2015). In addition, I included the sampling weight into the propensity score calculation to achieve unbiased treatment effect estimates that are generalisable to the target population of the original survey (Dugoff, Schuler and Stuart, 2014).

Another important step in estimating the propensity score is to choose the matching algorithm. In this study, I used several indicators that can test the algorithm's performance in bias reduction. The choice of the most appropriate algorithm was determined after taking into account the value of all indicators. The first indicator is the Likelihood Ratio test (LR-test) of the joint significance of all the control (matching) variables in the logit model using the propensity score as the weight. In other words, we need to re-run the propensity score model but use the estimated propensity score as the weight. Intuitively, once the sample has been properly weighted by its propensity score, all of the control variables should have no power in explaining the variation in treatment allocation (Wagstaff et al., 2009; Caliendo and Kopeinig, 2008). A significant LR-test means our matching method has not been adequately performed to achieve the balance between the treated and non-treated groups.

Other important indicators that are considered in this study include the following (Leuven and Sianesi, 2018):

- To quantify the bias, I calculated the mean bias, defined as the difference between the sample means in the matched treated and control subsamples as a percentage of the square root of the average of the sample variances in the treated and control groups. The median of bias is also calculated to account for outliers.
- B is the Rubin's B test which shows the absolute standardised difference of means of propensity score in the treated and matched non-treated groups. Good matching should have  $B < 25$ .

- R is the Rubin's R ratio of treated to matched non-treated variances of the propensity score index. It should be less than 2 and more than 0.5.
- I also calculated the ratio of the variance of the residuals orthogonal to the linear index of the propensity score in the treated group over the non-treated group for each covariate. Variables that have a ratio in the range of (0.5, 0.8) or (1.25, 2) are labelled as "Concern" whereas variables that have a ratio of <0.5 or >2 are labelled as "Bad" (Rubin, 2001).

The standard errors for the coefficients estimated from the propensity score matching need to be adjusted to reflect the sampling variance in the estimates of the propensity score (Caliendo and Kopeinig, 2008). One of the most common practices in dealing with this issue is the use of bootstrapping, as suggested by Lechner (2002). Bootstrapping is a common re-sampling method that allows for the estimation of the sampling variance of estimated parameters (Austin and Small, 2014). Bootstrapping involves re-estimating the propensity score and treatment effect calculation several times, often hundreds of times. Repeating the bootstrapping  $M$  times results in  $M$  estimated treatment effect. The distribution of the treatment effect from  $M$  bootstrap samples approximates to the sampling distribution of the population mean. In this chapter, standard errors for all PSM estimates were calculated using bootstrapping.

### 7.3.6 Difference-in-difference

While PSM is able to eliminate bias due to the observables, it is not sufficient for uncovering the programme's impact,  $G_{i,t}$ , in Equation 7-5. To uncover the true treatment effect, the second and third differences, i.e.  $\Delta\theta_t^P - \Delta\theta_t^{NP} + E(\Delta\varepsilon_{it}^P) - E(\varepsilon_{it}^{NP})$  need to disappear. Difference-in-difference (DID) is able to eliminate these unobservable biases using two important assumptions:

- (a) The time-specific unobservable factor exhibits the same trend between the treated and the untreated (i.e. the  $\theta$ 's change at the same speed). This will eliminate the first difference in unobservables, i.e.  $\Delta\theta_t^P - \Delta\theta_t^{NP}$ .

(b) The expectation of the change in the idiosyncratic errors is zero among both the treated and untreated. It refers to the second difference in the unobservables, i.e.  $\Delta\theta_t^P - \Delta\theta_t^{NP}$ .

If these two assumptions can be justified, DID may allow us to estimate the impact of a programme. Below I will explain the DID assumptions in more detail.

The first key assumption of the DID estimator is that the outcome trends would have been the same in both groups in the absence of the treatment. In an ideal experimental situation, we are usually interested in estimating the treatment effect for all participants (both treated and non-treated groups) and this is called the average treatment effect (ATE). However, in a non-experiment setting, ATE estimation requires strongly ignorable treatment assignment assumptions, namely unconfoundedness and overlap, and they are often violated in most applications (Imbens and Rubin, 2015). Another alternative is to calculate the treatment effect only for the treated group, which is called the average treatment effect on treated (ATT) and it requires weaker assumptions than ATE (Wooldridge, 2010). It follows from this that ATT can be calculated by taking the difference between the difference of outcome in the treatment group ( $Y_{1,2014} - Y_{1,2007}$ ) and the difference of outcome in the control group ( $Y_{0,2014} - Y_{0,2007}$ ), if the counterfactual outcome trend in the treatment group (i.e. if the treated remained untreated) was assumed to follow a similar slope as the control group. This assumption is often called the “parallel trend assumption”. Depending on the context, there may be several forms of this assumption and different approaches for testing it. We can test this assumption by calculating the effect of the treatment on the outcome before the programme was implemented (Angrist and Pischke, 2008). To test the parallel trend assumption in this analysis, I performed a placebo test by estimating the impact of JKN on the difference-in-difference estimates from IFLS 2000 and IFLS 2007. If the parallel trend assumption was valid, then the treatment variable should not have any effect on past outcomes. This assumption is violated if the obtained effects are statistically significant different at a 5 percent level.

The second type of unobservable bias due to time-varying unobservable factors cannot be eliminated by DID. To assess the scope of this hidden bias, I calculated the Rosenbaum bounds for the treatment effects. This test gives an indication of the extent of hidden bias that is required to undermine interpretation of the propensity score estimates (Rosenbaum, 2002). The bounding approach does not test the unconfoundedness assumption, because this would amount to testing that there are no (unobserved) variables that influence the selection into treatment. Instead, Rosenbaum bounds provide evidence on the degree to which any significance results hinge on this untestable assumption (Becker and Caliendo, 2007).

Only a single pre-intervention time point was chosen due to sample size consideration. Considering my strict inclusion criteria to identify the treated group, the inclusion of more than one pre-intervention period would likely to reduce the number of the treated group and reduce the statistical power of my analysis. Nevertheless, I utilised an additional pre-intervention period to test parallel trend assumption to check the robustness of my findings.

## **Section 7.4 Findings**

### **7.4.1 Descriptive statistics**

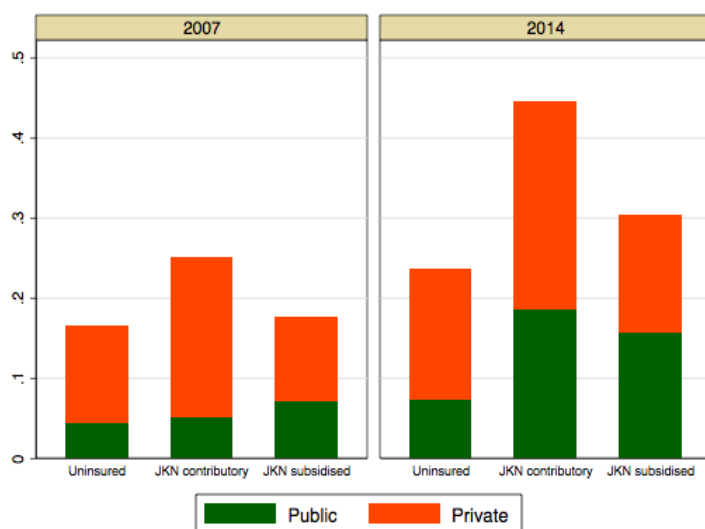
Table 7-1 presents a descriptive (unadjusted) table of the proportions of outpatient and inpatient use, whereas Figure 7-5 shows descriptive figures for the frequency of outpatient and inpatient visits. Compared with the uninsured, both the contributory and subsidised groups had a higher proportion and level of utilisation of outpatient and inpatient care in public and private facilities. This increase was observed at both the pre-reform (i.e. 2007) and post-reform (i.e. 2014) stages. The only exception was that the subsidised group had a slightly lower frequency of inpatient visits compared with the uninsured group in 2007 (see Figure 7-5.B). These results indicate a higher possibility of insurance selection bias for the contributory group, as they already had higher probability and frequency of utilisation before the JKN programme was introduced. Failing to tackle this insurance bias will lead to a misleading causal effect.

Table 7-1 Summary of utilisation profiles, by year and insurance status

Variables	Uninsured (N = 8,576)	JKN Contributory (N =9,82)	JKN Subsidised (N = 2,503)
<b>2007*</b>			
Probability of outpatient visits	12.0%	14.4%	13.2%
Probability of inpatient visits	2.0%	3.3%	1.7%
<b>2014</b>			
Probability of outpatient visits	14.5%	23.4%	17.4%
Probability of inpatient visits	2.6%	11.2%	4.2%

\*Since the JKN programme was introduced in 2014, the figures for JKN enrollees in 2007 represented their utilisation when they were still uninsured in 2007.

(A) Outpatient



(B) Inpatient

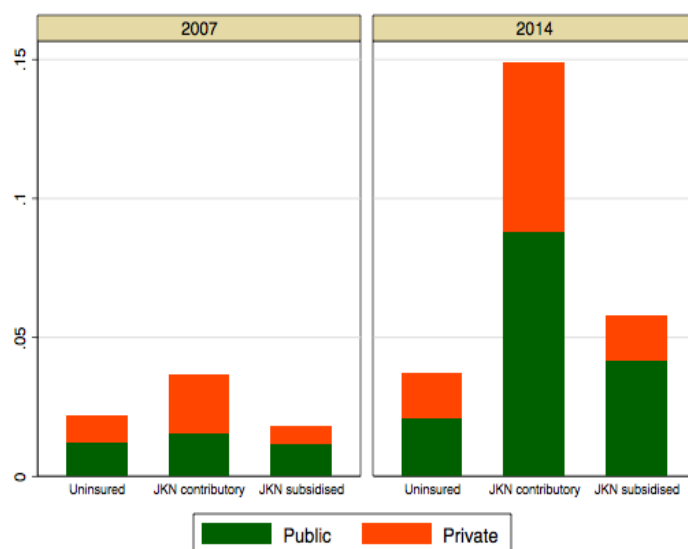


Figure 7-5 Number of visits by type of care, year and insurance status

Table 7-2 shows the characteristics of survey respondents by insurance status and year. Individuals belong to the JKN contributory group were younger, more likely to live in an urban area, wealthier, more likely to have completed higher education, and more likely to live in an area with more health facilities compared with the uninsured. Meanwhile, individuals belong to the JKN subsidised group were poorer, less likely to finish higher education, and more likely to live in an area with fewer health facilities compared to the uninsured.

Table 7-2 Descriptive statistics for control variables, by year and insurance status

Variables	2007			2014		
	Uninsured (N=8,564)	JKN Contributory (N=975)	JKN Subsidised (N=2,495)	Uninsured (N=8,564)	JKN Contributory (N=975)	JKN Subsidised (N=2,495)
Age (year)	37.18	33.8	37.33	43.7	40.33	43.8
Male (%)	45.7	42	45	46	42	45
Marital status						
Single (%)	18.9	24	15	8.7	9.5	6.3
Married (%)	72.5	72	77	78.5	82.2	81.2
Divorced/widowed (%)	8.6	4.2	8.4	12.8	8.5	12.5
Urban (%)	41.2	71.2	43.8	41.2	71.2	43.8
Highest education level						
Primary education (%)	41.1	22	51	40.5	21	49
Secondary education (%)	44.8	61	38	43.3	59.2	38
College (%)	1.8	6	1	2	4.9	1.1
Higher education (%)	3	8	1	5.5	12.6	2.1
No education (%)	8.6	3	9	8	2.2	9.1
Poorest – lowest quintile* (%)	20.1	9.2	32.6	20.4	7.1	32.2
Richest – highest quintile* (%)	16	35.2	5	17.2	39.6	7
No. of acute conditions	2.11	2.34	2.12	3.33	3.54	3.63
No. of chronic conditions	0.16	0.15	0.14	0.32	0.38	0.31
Any disability (%)	0.9	1.4	0.3	8.2	12	7.6
Density of outpatient health facilities **	0.2	0.549	0.11	0.242	0.631	0.135
Density of inpatient health facilities **	0.036	0.098	0.018	0.053	0.177	0.027
Recipient of unconditional cash transfer (%)	15.9	12.9	35	1	11.2	53

\*The asset index is calculated by combining variables reflecting the possession of certain durable assets and the characteristics of the dwellings via principal component analysis. A lower asset index represents lower socioeconomic status and vice versa.

\*\*Density variables were derived from the number of facilities divided by the village/township size in hectares (1 hectare = 10,000 m<sup>2</sup>)

From these descriptive statistics, it is clear that both the contributory and subsidised groups have different characteristics that may influence both utilisation variables and the uptake of insurance, hence the decision to separate these two groups. With regards to medical need measured by number of acute conditions, number of chronic conditions, and the presence of any disability, the contributory group is likely to have a greater need compared with the uninsured. The subsidised group, however, does not always show a higher medical need compared to the uninsured, either at a similar level or lower. This may be an indication that the insurance selection bias for the subsidised group is not large. Furthermore, the supply-side variables, measured by the density of health care facilities, may influence the insurance selection bias within the contributory group. Contributory group members are more likely to live in an area which has a higher density of health care facilities than the uninsured. This finding may be explained by a higher probability of living in an urban area, which tends to have more clinics and hospitals, within the contributory group. Interestingly, although both the subsidised and the uninsured groups tend to live in rural areas, the subsidised group is more likely to live in an area with a lower density of health care facilities.

#### 7.4.2 Naïve estimator

In this sub-section, I will show the effect of the JKN programme without taking into account insurance selection bias explicitly as a comparator to findings based on PSM-DID later in the next sub-section. Logit model and negative binomial regression model are used to model binary outcome variable and count data outcome variable, respectively. The logit model follows

*Equation 7-6*

$$\text{Ln} \left( \frac{p_i}{1-p_i} \right) = \alpha + \delta_i T_i + \sum_{j=1}^J \beta_j X_{ij} + u_i, \text{ with: } \Pr(Y_i = 1 | X_i) = p_i$$

$Y_i$  refers to my binary outcome variable, i.e. the proportion of utilising care;  $X_{ij}$  includes all control variables described in sub-section 7.33 and  $\beta_{ij}$  is the coefficient for each  $X_{ij}$ ;  $\alpha$  is the model intercept, and  $u_i$  captures random error term.  $T_i$  represents the insurance status with  $T = 1$  as being insured and  $T = 0$  as being uninsured. Thus,  $\delta_i$  can be interpreted as the log odds ratio of the JKN programme impact comparing the



insured group to the uninsured. Given the slope's coefficient in logit model no longer has a marginal effect interpretation, I calculated the partial effect at the average (PEA) referring to the marginal effect at the mean of covariates (Wooldridge, 2013). In addition, the count data variable, i.e. the number of visits, is modelled by negative binomial regression model, which is similar to Poisson model but allows for over-dispersion issue by assuming that there will be random variability among individuals who have the same predicted value (Cameron and Trivedi, 2010).

1Table 7-3 Naive estimator for utilisation of health care

<b>Variables</b>	<b>Contributory</b>	<b>Subsidised</b>
<b>Outpatient care</b>		
Probability of utilising any outpatient visit in the past month (%)	6.95*** (1.11)	2.35*** (0.95)
Number of total visits (all)	0.17*** (0.02)	0.04*** (0.02)
Number of total visits (public)	0.09*** (0.01)	0.06*** (0.01)
Number of total visits (private)	0.08*** (0.02)	-0.02 (0.02)
<b>Inpatient care</b>		
Probability of utilising any inpatient visit in the past year (%)	4.6*** (0.45)	0.96** (0.23)
Number of total visits (all)	0.07*** (0.01)	0.02*** (0.01)
Number of total visits (public)	0.05*** (0.01)	0.02*** (0.37)
Number of total visits (private)	0.02*** (0.004)	-0.001 (0.02)

Note: Standard errors in parentheses have been adjusted for complex survey design. \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

1Table 7-3 shows the results of the logit model for the binary outcome of outpatient and inpatient visits and the negative binomial regression model for the number of visits to public and private facilities. All coefficients show the marginal effect of the JKN programme. Overall, both the contributory and subsidised groups showed significantly higher probability and frequency of utilisation for both outpatient and inpatient care, especially in public facilities. The subsidised group showed no increased visits to private facilities, but the contributory group, on average, made 0.08 more outpatient visits and 0.02 more inpatient visits compared with the

uninsured. Naïve estimators are not able to estimate the true causal effect because of their failure to tackle insurance selection bias. In the next sub-section, I will begin by presenting the results of the PSM-DID analysis, which is argued to be more robust than the naïve estimator.

#### **7.4.3 Diagnostic tests of matching algorithms**

Firstly, I provided a comparison of the different matching algorithms to select the best one for my PSM-DID analysis. Based on the quality indicators in judging the extent of bias reduction from each matching algorithm in

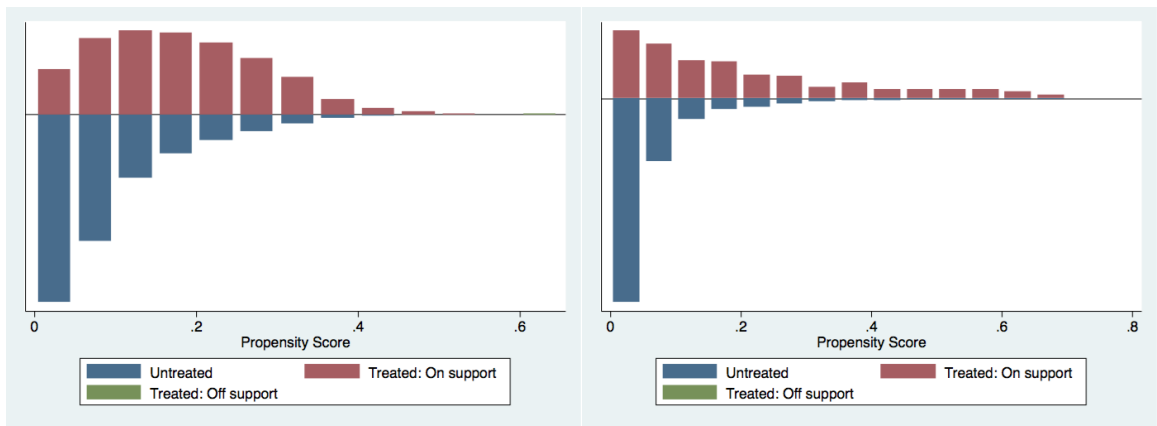
Table 7-4, radius matching and kernel matching perform better than the others. I decided to choose Kernel matching – its validity in terms of using bootstrapping to obtain the corrected standard errors is well established (Heckman, Ichimura, and Todd, 1998; Abadie and Imbens, 2008).

Figure 7-6 (a) and (b) show the histograms for the propensity scores after matching using the kernel matching. Despite its skewed distribution, there are ample overlaps between the treated and the control group. This implies that the matching has successfully retained adequate samples to avoid attrition bias from the cases of off-support. Figure 7-6 (c) and (d) show the extent to which matching has reduced the bias in our analysis. Both graphs show that after matching, the standardised percentage of bias across covariates has been reduced to near zero.

Table 7-4 Comparison of the bias across different matching techniques (command = psmatch2 and ptest)

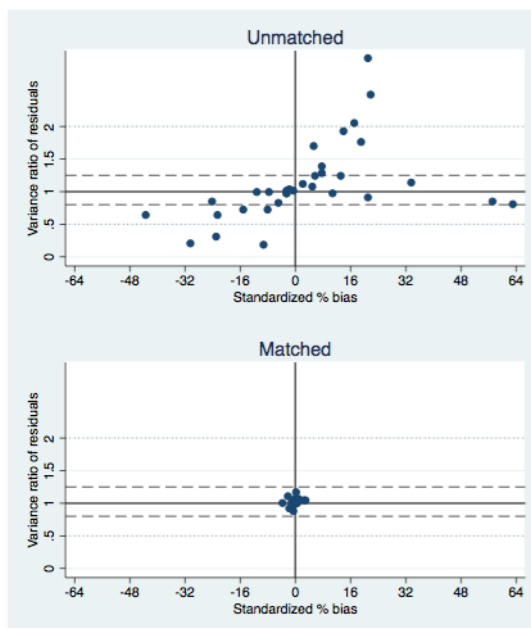
Matching technique	LR chi <sup>2</sup>	p-value	Mean Bias	B	R	% concern	% bad	Off support
<b>Contributory group</b>								
Unmatched	743.34	<0.01	16.20	97.7*	0.72	30	18	-
1 to 1 matching	11.87	1.00	1.90	15.50	1.01	6	0	0
1 to 1 no replacement	11.70	1.00	2.20	15.40	1.05	3	0	0
Nearest neighbour matching (n=5) caliper 0.01	4.10	1.00	1.20	9.10	1.05	3	0	1
Radius caliper 0.01	1.63	1.00	0.70	5.80	1.03	0	0	1
Kernel (bandwidth=0.01)	1.68	1.00	0.70	5.80	1.04	0	0	1
Kernel normal (bandwidth=0.01)	11.87	1.00	1.90	15.50	1.01	6	0	0
Mahalanobis	23.65	0.89	1.80	22.00	1.35	6	0	0
<b>Subsidised group</b>								
Unmatched	862	<0.01	12.7	115.6*	1.81	34	12	-
1 to 1 matching	13.26	0.998	2.7	19.1	1.11	12	3	0
1 to 1 no replacement	14.03	0.998	3.1	19.7	1.15	25	0	0
Nearest neighbour matching (n=5) caliper 0.01	4.30	1.00	1.50	10.90	1.14	6	0	1
Radius caliper 0.01	2.90	1.00	1.20	8.90	0.95	0	0	1
Kernel (bandwidth=0.01)	2.93	1.00	1.20	9.00	0.95	0	0	1
Kernel normal (bandwidth=0.01)	13.26	1.00	2.70	19.10	1.11	12	3	0
Mahalanobis	32.74	0.43	3.10	30.2*	1.30	3	0	0

\* if B>25%, R outside [0.5; 2]

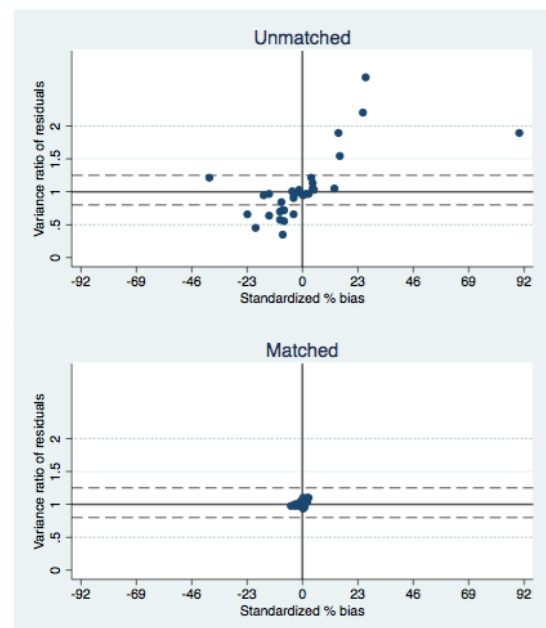


(a)

(b)



(c)



(d)

Figure 7-6 Support and balance after kernel matching

(a) shows support between treated and untreated for the contributory group whereas (b) is for the subsidised group.

(c) and (d) show the reduced bias before and after matching for the contributory group and subsidised group respectively.

#### 7.4.4 Impact estimates from PSM-DID

Table 7-5 reports the results of the adjusted analysis of outpatient and inpatient visits based on PSM with kernel matching and DID following Equation 7-5. This was implemented by (1) calculating the first difference, that is, the difference in the mean outcomes between 2007 and 2014 for each group; and then (2) taking the difference of the first differences between the treated and untreated groups to estimate the average treatment effect on the treated (ATT). The first column shows the ATT for the contributory group. The contributory group had 7.9 percent (95% CI: 4.3% - 11.4%) and 8.2 percent (95% CI: 5.9% - 10.5%) higher probabilities of using outpatient and inpatient care, respectively, compared with the uninsured. Furthermore, the contributory group had 0.16 (95% CI: 0.05 - 0.27) more outpatient visits per person per month and 0.1 (95% CI: 0.08 - 0.14) more inpatient visits per person per year compared to the uninsured. This higher number of total visits was likely to occur in public facilities. While the number of outpatient visits to private facilities was not significantly affected, the number of inpatient visits to private facilities increased significantly.

The fourth column shows the ATT for the subsidised group. It appears that the JKN programme increased the probability of seeking care at outpatient facilities among the subsidised group by 2 percent (95% CI: -0.4% - 4.3%), but this effect is not significant at 10 percent level. Meanwhile, the subsidised group also increased their probability of having any inpatient visit by 1.8 percent (95% CI: 0.7% - 2.8%) compared with the uninsured. In addition, the JKN subsidised group spent more number of visits to public facilities for both outpatient and inpatient care compared to the uninsured. Overall, the estimates obtained from the subsidised group were smaller in magnitude than the estimates from the contributory group.

Table 7-5 Average treatment effects on treated (ATT) estimates for both contributory and subsidised groups relative to the uninsured

Outcomes	Contributory			Subsidised		
	ATT (1)	95% CI (2)	95% CI (3)	ATT (4)	95% CI (5)	95% CI (6)
<b>Outpatient care</b>						
Probability of having outpatient visits	7.87%***	4.32%	11.43%	1.96%	-0.36%	4.27%
Number of visits (all)	0.158***	0.046	0.269	0.063***	0.016	0.110
Number of visits (public)	0.115***	0.072	0.158	0.059***	0.024	0.094
Number of visits (private)	0.043	-0.050	0.135	0.004	-0.028	0.036
<b>Inpatient care</b>						
Probability of having inpatient visits	8.18%***	5.89%	10.46%	1.76%***	0.70%	2.82%
Number of visits (all)	0.109***	0.079	0.138	0.023***	0.006	0.040
Number of visits (public)	0.073***	0.054	0.091	0.018***	0.004	0.033
Number of visits (private)	0.036***	0.010	0.062	0.005	-0.005	0.014

Note: ATT is calculated by simply taking the difference between the treated (either contributory or subsidised) and the control (uninsured) groups. The treated group was matched with the control group through kernel Epanechnikov matching with bandwidth = 0.01. The standard errors were calculated by bootstrapping with 200 replications. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

	Probability of having outpatient visits (%)	Number of outpatient visits (all)	Number of outpatient visits (public)	Number of outpatient visits (private)	Probability of having inpatient visits (%)	Number of inpatient visits (all)	Number of inpatient visits (public)	Number of inpatient visits (private)
<b>Subsidised Group</b>								
Q1 (N = 2547)	-1.1 (2.1)	0.013 (0.046)	0.009 (0.039)	0.004 (0.023)	0.015 (0.010)	0.010 (0.012)	0.012 (0.009)	-0.002 (0.006)
Q2 (N = 2525)	6.9*** (2.7)	0.126** (0.060)	0.112*** (0.037)	0.015 (0.034)	-0.004 (0.013)	-0.001 (0.014)	0.010 (0.014)	-0.011 (0.006)
Q3 (N = 2324)	0.6 (2.1)	0.056 (0.047)	0.087* (0.045)	-0.031 (0.033)	0.032*** (0.011)	0.042** (0.021)	0.033* (0.019)	0.009 (0.008)
Q4 (N= 2011)	1.3 (2.4)	0.047 (0.044)	0.066* (0.034)	-0.020 (0.033)	0.030** (0.014)	0.049* (0.028)	0.039 (0.027)	0.010 (0.007)
Q5 (N= 1653)	9.3* (5.4)	0.180* (0.101)	0.044 (0.060)	0.136* (0.081)	0.017 (0.023)	0.043 (0.049)	0.009 (0.029)	0.034 (0.047)
Urban (N = 4545)	3.2 (2.1)	0.112*** (0.038)	0.114*** (0.028)	-0.002 (0.027)	0.016* (0.009)	0.026* (0.016)	0.019 (0.015)	0.007 (0.008)
Rural (N = 6525)	1.1 (0.013)	0.025 (0.037)	0.019 (0.024)	0.006 (0.029)	0.017** (0.007)	0.019* (0.011)	0.018** (0.009)	0.001 (0.005)
<b>Contributory Group</b>								
Q1 (N = 1814)	-2.4 (6.3)	-0.018 (0.112)	0.052 (0.056)	-0.070 (0.091)	0.041 (0.047)	0.046 (0.056)	0.006 (0.035)	0.040 (0.029)
Q2 (N = 1950)	11.3** (5.6)	0.312 (0.194)	0.173* (0.099)	0.139 (0.142)	0.081** (0.029)	0.184*** (0.061)	0.117** (0.048)	0.067 (0.048)

Table 7-6	Q3	10.6***	0.172	0.176***	-0.005	0.099***	0.113**	0.083**	0.030
	(N = 1979)	(3.1)	(0.279)	(0.065)	(0.279)	(0.034)	(0.050)	(0.038)	(0.025)
	Q4	8.8**	0.081	0.060*	0.021	0.095***	0.126***	0.090**	0.036**
	(N = 1933)	(3.9)	(0.073)	(0.033)	(0.066)	(0.029)	(0.041)	(0.036)	(0.015)
	Q5	8.3**	0.207**	0.126***	0.081	0.071***	0.080***	0.054***	0.026
	(N = 1866)	(3.8)	(0.081)	(0.037)	(0.066)	(0.019)	(0.025)	(0.012)	(0.023)
	Urban	8.5***	0.146**	0.119***	0.026	0.097***	0.128***	0.082***	0.046***
	(N = 4224)	(2.1)	(0.066)	(0.025)	(0.060)	(0.015)	(0.021)	(0.016)	(0.015)
	Rural	6.8**	0.199*	0.109***	0.090	0.044**	0.063**	0.051***	0.013
	(N = 5327)	(3.2)	(0.111)	(0.031)	(0.093)	(0.018)	(0.031)	(0.015)	(0.020)

demonstrates the impact of the JKN programme on the contributory group and the subsidised group stratified by asset index quintiles. The impact on the contributory group was observed across all quintiles, except the poorest (1<sup>st</sup> quintile). A higher impact among the wealthiest was expected because they were more likely to afford the premium. Meanwhile, the effects on the subsidised group showed a different pattern: increased outpatient utilisation was higher in the second quintile but the effect on inpatient utilisation was stronger among the third and fourth quintiles. No effect was observed among the poorest quintile. In addition, the positive impact among more affluent individuals may confirm the suspicion that some of the subsidies were misdirected. The premium subsidy within the JKN programme was targeted to reach the 40-percent poorest population only.

The impact estimates were also stratified by urban and rural area (see

	Probability of having outpatient visits (%)	Number of outpatient visits (all)	Number of outpatient visits (public)	Number of outpatient visits (private)	Probability of having inpatient visits (%)	Number of inpatient visits (all)	Number of inpatient visits (public)	Number of inpatient visits (private)
Subsidised Group								
Q1	-1.1	0.013	0.009	0.004	0.015	0.010	0.012	-0.002
(N = 2547)	(2.1)	(0.046)	(0.039)	(0.023)	(0.010)	(0.012)	(0.009)	(0.006)
Q2	6.9***	0.126**	0.112***	0.015	-0.004	-0.001	0.010	-0.011
(N = 2525)	(2.7)	(0.060)	(0.037)	(0.034)	(0.013)	(0.014)	(0.014)	(0.006)
Q3	0.6	0.056	0.087*	-0.031	0.032***	0.042**	0.033*	0.009
(N = 2324)	(2.1)	(0.047)	(0.045)	(0.033)	(0.011)	(0.021)	(0.019)	(0.008)
Q4	1.3	0.047	0.066*	-0.020	0.030**	0.049*	0.039	0.010
(N = 2011)	(2.4)	(0.044)	(0.034)	(0.033)	(0.014)	(0.028)	(0.027)	(0.007)
Q5	9.3*	0.180*	0.044	0.136*	0.017	0.043	0.009	0.034
(N = 1653)	(5.4)	(0.101)	(0.060)	(0.081)	(0.023)	(0.049)	(0.029)	(0.047)
Urban	3.2	0.112***	0.114***	-0.002	0.016*	0.026*	0.019	0.007
(N = 4545)	(2.1)	(0.038)	(0.028)	(0.027)	(0.009)	(0.016)	(0.015)	(0.008)
Rural	1.1	0.025	0.019	0.006	0.017**	0.019*	0.018**	0.001
(N = 6525)	(0.013)	(0.037)	(0.024)	(0.029)	(0.007)	(0.011)	(0.009)	(0.005)
Contributory Group								
Q1	-2.4	-0.018	0.052	-0.070	0.041	0.046	0.006	0.040



(N = 1814)	(6.3)	(0.112)	(0.056)	(0.091)	(0.047)	(0.056)	(0.035)	(0.029)
Q2	11.3**	0.312	0.173*	0.139	0.081**	0.184***	0.117**	0.067
(N = 1950)	(5.6)	(0.194)	(0.099)	(0.142)	(0.029)	(0.061)	(0.048)	(0.048)
Q3	10.6***	0.172	0.176***	-0.005	0.099***	0.113**	0.083**	0.030
(N = 1979)	(3.1)	(0.279)	(0.065)	(0.279)	(0.034)	(0.050)	(0.038)	(0.025)
Q4	8.8**	0.081	0.060*	0.021	0.095***	0.126***	0.090**	0.036**
(N = 1933)	(3.9)	(0.073)	(0.033)	(0.066)	(0.029)	(0.041)	(0.036)	(0.015)
Q5	8.3**	0.207**	0.126***	0.081	0.071***	0.080***	0.054***	0.026
(N = 1866)	(3.8)	(0.081)	(0.037)	(0.066)	(0.019)	(0.025)	(0.012)	(0.023)
Urban	8.5***	0.146**	0.119***	0.026	0.097***	0.128***	0.082***	0.046***
(N = 4224)	(2.1)	(0.066)	(0.025)	(0.060)	(0.015)	(0.021)	(0.016)	(0.015)
Rural	6.8**	0.199*	0.109***	0.090	0.044**	0.063**	0.051***	0.013
(N = 5327)	(3.2)	(0.111)	(0.031)	(0.093)	(0.018)	(0.031)	(0.015)	(0.020)

Table 7-6). Among the contributory group, enrolees from both rural and urban areas showed a similar pattern of positive and significant effects on both outpatient and inpatient utilisation. Subsidised individuals living in rural areas showed a positive impact on inpatient utilisation, whereas those living in urban areas showed a positive impact only on the frequency of outpatient utilisation in public facilities.

	Probability of having outpatient visits (%)	Number of outpatient visits (all)	Number of outpatient visits (public)	Number of outpatient visits (private)	Probability of having inpatient visits (%)	Number of inpatient visits (all)	Number of inpatient visits (public)	Number of inpatient visits (private)
<b>Subsidised Group</b>								
Q1	-1.1	0.013	0.009	0.004	0.015	0.010	0.012	-0.002
(N = 2547)	(2.1)	(0.046)	(0.039)	(0.023)	(0.010)	(0.012)	(0.009)	(0.006)
Q2	6.9***	0.126**	0.112***	0.015	-0.004	-0.001	0.010	-0.011
(N = 2525)	(2.7)	(0.060)	(0.037)	(0.034)	(0.013)	(0.014)	(0.014)	(0.006)
Q3	0.6	0.056	0.087*	-0.031	0.032***	0.042**	0.033*	0.009
(N = 2324)	(2.1)	(0.047)	(0.045)	(0.033)	(0.011)	(0.021)	(0.019)	(0.008)
Q4	1.3	0.047	0.066*	-0.020	0.030**	0.049*	0.039	0.010
(N = 2011)	(2.4)	(0.044)	(0.034)	(0.033)	(0.014)	(0.028)	(0.027)	(0.007)
Q5	9.3*	0.180*	0.044	0.136*	0.017	0.043	0.009	0.034
(N = 1653)	(5.4)	(0.101)	(0.060)	(0.081)	(0.023)	(0.049)	(0.029)	(0.047)
Urban	3.2	0.112***	0.114***	-0.002	0.016*	0.026*	0.019	0.007
(N = 4545)	(2.1)	(0.038)	(0.028)	(0.027)	(0.009)	(0.016)	(0.015)	(0.008)
Rural	1.1	0.025	0.019	0.006	0.017**	0.019*	0.018**	0.001
(N = 6525)	(0.013)	(0.037)	(0.024)	(0.029)	(0.007)	(0.011)	(0.009)	(0.005)
<b>Contributory Group</b>								
Q1	-2.4	-0.018	0.052	-0.070	0.041	0.046	0.006	0.040
(N = 1814)	(6.3)	(0.112)	(0.056)	(0.091)	(0.047)	(0.056)	(0.035)	(0.029)
Q2	11.3**	0.312	0.173*	0.139	0.081**	0.184***	0.117**	0.067
(N = 1950)	(5.6)	(0.194)	(0.099)	(0.142)	(0.029)	(0.061)	(0.048)	(0.048)
Q3	10.6***	0.172	0.176***	-0.005	0.099***	0.113**	0.083**	0.030
(N = 1979)	(3.1)	(0.279)	(0.065)	(0.279)	(0.034)	(0.050)	(0.038)	(0.025)
Q4	8.8**	0.081	0.060*	0.021	0.095***	0.126***	0.090**	0.036**
(N = 1933)	(3.9)	(0.073)	(0.033)	(0.066)	(0.029)	(0.041)	(0.036)	(0.015)
Q5	8.3**	0.207**	0.126***	0.081	0.071***	0.080***	0.054***	0.026

Table 7-6	(N = 1866)	(3.8)	(0.081)	(0.037)	(0.066)	(0.019)	(0.025)	(0.012)	(0.023)
PSM-DID findings on the impact	Urban	8.5***	0.146**	0.119***	0.026	0.097***	0.128***	0.082***	0.046***
	(N = 4224)	(2.1)	(0.066)	(0.025)	(0.060)	(0.015)	(0.021)	(0.016)	(0.015)
	Rural	6.8**	0.199*	0.109***	0.090	0.044**	0.063**	0.051***	0.013
	(N = 5327)	(3.2)	(0.111)	(0.031)	(0.093)	(0.018)	(0.031)	(0.015)	(0.020)

of health insurance on both the subsidised and contributory groups, by socioeconomic status quintiles and urban/rural location

ATT is calculated by simply taking the difference between the treated (either contributory or subsidised) and the control (uninsured) group. The treated group was matched with the control group through kernel Epanechnikov matching with bandwidth = 0.01. The reported standard errors were calculated by bootstrapping with 200 replications. Quintiles are based on the asset index in 2007. Standard errors are in parentheses. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table 7-7 demonstrates the heterogeneity of the JKN effect by supply-side factors, measured by the density of health care facilities. The calculation of density variables was done separately for outpatient and inpatient care. After this, I sorted the samples from the lowest to the highest based on the density variables and divided the samples into four equal group (quartiles). Almost no significant effect was observed in the area with a low density of health care facilities. In the high-density area, however, the effect on inpatient visits was large and significant for both the contributory and subsidised groups. This further confirms the suggestion that the effect of health insurance can only be realised given the availability of nearby health care facilities.

Table 7-7 Heterogeneity of the JKN impact, by density of health care facilities

	Probability of any outpatient care (%)	Number of outpatient visits (total)	Number of outpatient visits (public)	Number of outpatient visits private	Probability of any inpatient care (%)	Number of inpatient visits (total)	Number of inpatient visits (public)	Number of inpatient visits private
<b>Contributory group</b>								
Q1 (Lowest)	1.6 (3.9)	0.097 (0.130)	0.046 (0.048)	0.051 (0.136)	2.5 (2.1)	0.050 (0.038)	0.038 (0.025)	0.013 (0.022)
Q2	11.1*** (3.9)	0.2** (0.082)	0.098*** (0.036)	0.102 (0.066)	10.2*** (2.5)	0.093** (0.037)	0.088*** (0.026)	0.002 (0.026)
Q3	12.9*** (4.1)	0.243** (0.108)	0.143*** (0.054)	0.099 (0.098)	8.3*** (2.3)	0.084*** (0.027)	0.046** (0.019)	0.039 (0.020)
Q4 (Highest)	3.5 (3.1)	0.067 (0.107)	0.148*** (0.049)	-0.081 (0.101)	10.3*** (2.6)	0.176*** (0.046)	0.105*** (0.027)	0.076*** (0.025)

Subsidised group

Q1	1.7	0.068	0.017	0.051	1.6	0.012	-0.001	0.008
(Lowest)	(2.2)	(0.057)	(0.041)	(0.033)	(1.1)	(0.014)	(0.011)	(0.009)
Q2	1.4	0.016	0.053**	-0.037	0.8	0.005	0.023	-0.013
	(2.1)	(0.042)	(0.024)	(0.027)	(1.1)	(0.022)	(0.019)	(0.009)
Q3	0.2	0.029	0.030	-0.001	1.3	0.024*	0.021*	0.003
	(2.3)	(0.041)	(0.028)	(0.027)	(1.2)	(0.014)	(0.013)	(0.005)
Q4	4.8	0.155**	0.133***	0.021	3.1***	0.046***	0.029**	0.021
(Highest)	(3.7)	(0.060)	(0.045)	(0.043)	(1.1)	(0.017)	(0.011)	(0.015)

*The reported standard errors were calculated by bootstrapping with 200 replications. \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$*

#### 7.4.5 Robustness check

In the first instance, I checked the robustness of the impact estimates using different caliper of kernel matching. Table 7-8 shows that overall, the impact estimates for the contributory group are not sensitive to the size of the bandwidth for calculating the distance in kernel matching. The magnitude and the significance of the estimates seemed stable even at bandwidth 0.001. Meanwhile, standard errors for the subsidised group were quite sensitive to a smaller bandwidth. Most of the impact estimates were no longer significant at a level of 5 percent but they were still significant at 10 percent. Overall, it seems that the expansion of public health insurance to the previously uninsured has had a profound effect on increasing the utilisation of inpatient care.

Secondly, I checked the potential influence of the unobserved non-fixed confounders on the estimates by calculating Rosenbaum bounds (detailed results can be seen in Table A-3 and A-4 in the appendices). It appears that the effect on the probability of utilising inpatient care is more stable than the effect on the probability of using outpatient services for the contributory group. However, the impact on the

subsidised group is more sensitive to the unobserved non-fixed confounders for the probability of using both outpatient and inpatient services. The impacts on total visits for both groups are very sensitive to this unobserved bias.

Thirdly, I also ran a placebo regression to test the parallel trend assumption by using data from IFLS 2000 and IFLS 2007. The same PSM-DID model was estimated using the mean difference of utilisation variables from IFLS 2000 and 2007. Parallel trend assumption is valid if none of the outcomes in this placebo test are significant. From **Error! Reference source not found.**, it appears that none of the outcome variables show any significant effect, taken as a p-value equal to or less than 0.05. The PSM-DID model therefore passed the parallel trend assumption.

Table 7-8 Sensitivity analysis to different matching bandwidths for Kernel Epanechnikov

Choice of bandwidth	Probability of any outpatient care	Number of outpatient visits (total)	Number of outpatient visits (public)	Number of outpatient visits (private)	Probability of any inpatient care	Number of inpatient visits (total)	Number of inpatient visits (public)	Number of inpatient visits (private)
<b>JKN Subsidised</b>								
0.05	0.030 (0.021)	0.097** (0.045)	0.070** (0.032)	0.032 (0.025)	0.028*** (0.010)	0.038** (0.016)	0.030** (0.013)	0.013 (0.010)
0.005	0.030 (0.024)	0.104** (0.048)	0.072** (0.035)	0.034 (0.028)	0.028** (0.012)	0.039** (0.018)	0.030** (0.014)	0.014 (0.011)
0.001	0.031 (0.025)	0.111** (0.056)	0.069* (0.040)	0.040 (0.033)	0.029*** (0.011)	0.039* (0.021)	0.032* (0.017)	0.011 (0.010)
<b>JKN Contributory</b>								
0.05	0.075*** (0.018)	0.127 (0.067)	0.115*** (0.026)	0.040 (0.053)	0.084*** (0.012)	0.108*** (0.018)	0.073*** (0.012)	0.036*** (0.012)
0.005	0.077*** (0.019)	0.128** (0.058)	0.115*** (0.022)	0.043 (0.051)	0.085*** (0.013)	0.109*** (0.019)	0.072*** (0.013)	0.037*** (0.011)
0.001	0.080*** (0.020)	0.140 (0.074)	0.119*** (0.028)	0.050 (0.064)	0.087*** (0.013)	0.112*** (0.019)	0.072*** (0.014)	0.040*** (0.011)

The reported standard errors were calculated by bootstrapping with 200 replications. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table 7-9 Placebo test from IFLS 2000

	ATT	p-value
<b>JKN Subsidised</b>		

Prob. of any outpatient care	0.76%	0.59
Number of outpatient visits (total)	0.018	0.45
Number of outpatient visits (public)	0.021	0.17
Number of outpatient visits (private)	-0.003	0.87
Prob. of any inpatient care	-0.95%	0.08
Number of inpatient visits (total)	-0.010	0.11
Number of inpatient visits (public)	-0.003	0.40
Number of inpatient visits (private)	-0.007	0.06

**JKN Contributory**

Prob. of any outpatient care	-0.62%	0.62
Number of outpatient visits (total)	-0.007	0.73
Number of outpatient visits (public)	0.010	0.50
Number of outpatient visits (private)	-0.017	0.28
Prob. of any inpatient care	-0.64%	0.17
Number of inpatient visits (total)	-0.007	0.20
Number of inpatient visits (public)	-0.002	0.44
Number of inpatient visits (private)	-0.003	0.41

*All outcome variables are taken from IFLS 2000. ATT is calculated by simply taking the difference between the treated (either contributory or subsidised) and the control (uninsured) groups. Standard error is calculated via bootstrap 200 replications. The treated group was matched with the control group through kernel Epanechnikov with bandwidth = 0.01. The parallel trend assumption can be upheld if the ATT from IFLS 2000 shows no significant effect with an assumed type-1 error taken at a level of 5%.*

Fourth, considering some of the respondents were interviewed in the period of September – December 2014, those people might have reported inpatient visits that happened before 2014. Thus, I also repeated the PSM-DID analysis for the inpatient outcomes for individuals interviewed in 2015 only. Based on Table 7-10, focusing on respondents interviewed in 2015 the JKN still has a positive impact on probability of seeking outpatient and inpatient care, for both contributory and subsidised groups with similar magnitude compared to overall sample in

	Probability of having outpatient visits (%)	Number of outpatient visits (all)	Number of outpatient visits (public)	Number of outpatient visits (private)	Probability of having inpatient visits (%)	Number of inpatient visits (all)	Number of inpatient visits (public)	Number of inpatient visits (private)
<b>Subsidised Group</b>								
Q1 (N = 2547)	-1.1 (2.1)	0.013 (0.046)	0.009 (0.039)	0.004 (0.023)	0.015 (0.010)	0.010 (0.012)	0.012 (0.009)	-0.002 (0.006)
Q2 (N = 2525)	6.9*** (2.7)	0.126** (0.060)	0.112*** (0.037)	0.015 (0.034)	-0.004 (0.013)	-0.001 (0.014)	0.010 (0.014)	-0.011 (0.006)
Q3 (N = 2324)	0.6 (2.1)	0.056 (0.047)	0.087* (0.045)	-0.031 (0.033)	0.032*** (0.011)	0.042** (0.021)	0.033* (0.019)	0.009 (0.008)
Q4 (N= 2011)	1.3 (2.4)	0.047 (0.044)	0.066* (0.034)	-0.020 (0.033)	0.030** (0.014)	0.049* (0.028)	0.039 (0.027)	0.010 (0.007)
Q5 (N= 1653)	9.3* (5.4)	0.180* (0.101)	0.044 (0.060)	0.136* (0.081)	0.017 (0.023)	0.043 (0.049)	0.009 (0.029)	0.034 (0.047)

Table 7-6.	Urban	3.2	0.112***	0.114***	-0.002	0.016*	0.026*	0.019	0.007
	(N = 4545)	(2.1)	(0.038)	(0.028)	(0.027)	(0.009)	(0.016)	(0.015)	(0.008)
	Rural	1.1	0.025	0.019	0.006	0.017**	0.019*	0.018**	0.001
	(N = 6525)	(0.013)	(0.037)	(0.024)	(0.029)	(0.007)	(0.011)	(0.009)	(0.005)
<b>Contributory Group</b>									
Table 7-10	Q1	-2.4	-0.018	0.052	-0.070	0.041	0.046	0.006	0.040
	(N = 1814)	(6.3)	(0.112)	(0.056)	(0.091)	(0.047)	(0.056)	(0.035)	(0.029)
	Q2	11.3**	0.312	0.173*	0.139	0.081**	0.184***	0.117**	0.067
	(N = 1950)	(5.6)	(0.194)	(0.099)	(0.142)	(0.029)	(0.061)	(0.048)	(0.048)
	Q3	10.6***	0.172	0.176***	-0.005	0.099***	0.113**	0.083**	0.030
	(N = 1979)	(3.1)	(0.279)	(0.065)	(0.279)	(0.034)	(0.050)	(0.038)	(0.025)
	Q4	8.8**	0.081	0.060*	0.021	0.095***	0.126***	0.090**	0.036**
	(N = 1933)	(3.9)	(0.073)	(0.033)	(0.066)	(0.029)	(0.041)	(0.036)	(0.015)
	Q5	8.3**	0.207**	0.126***	0.081	0.071***	0.080***	0.054***	0.026
	(N = 1866)	(3.8)	(0.081)	(0.037)	(0.066)	(0.019)	(0.025)	(0.012)	(0.023)
Urban	8.5***	0.146**	0.119***	0.026	0.097***	0.128***	0.082***	0.046***	
(N = 4224)	(2.1)	(0.066)	(0.025)	(0.060)	(0.015)	(0.021)	(0.016)	(0.015)	
Rural	6.8**	0.199*	0.109***	0.090	0.044**	0.063**	0.051***	0.013	
(N = 5327)	(3.2)	(0.111)	(0.031)	(0.093)	(0.018)	(0.031)	(0.015)	(0.020)	

*Sensitivity analysis of the JKN effect on inpatient utilisation, by the year of interview (2015 only)*

	Treatment effect	P-value	95% CI (Lower - Upper)	
<b>Contributory group</b>				
Probability of having inpatient visits (%)	7.03%	<0.001	4.01%	10.05%
Number of inpatient visits (all)	0.09	<0.001	0.05	0.12
Number of inpatient visits (public)	0.06	<0.001	0.04	0.08
Number of inpatient visits (private)	0.03	0.01	0.01	0.06
<b>Subsidised group</b>				
Probability of having inpatient visits (%)	2.31%	0.01	0.00%	4.00%
Number of inpatient visits (all)	0.03	0.04	0.00	0.05
Number of inpatient visits (public)	0.01	0.13	0.00	0.03
Number of inpatient visits (private)	0.01	0.11	0.00	0.03

## Section 7.5 Discussion

This chapter has analysed the impact of the JKN programme on access to care measured by individual's health care utilisation. Two treatment groups were identified based on their ability to pay the premium: a contributory group and a subsidised group. Each treatment group was compared to the uninsured group separately. This study's findings suggest that the JKN programme has improved access to both inpatient and outpatient care. It has increased the probability of individuals seeking outpatient and inpatient care as well as the volume of care provided. This impact is stronger among the contributory group, which likely comes from the wealthier and more educated population. This finding is consistent with the relevant theory, as well as evidence from other countries (Bernal, Carpio and Klein, 2014; Miller, Pinto and Vera-Hernandez, 2013; Nguyen, 2012; Robyn et al., 2012). The contributory group represents self-selected participation in JKN while the subsidised group had limited power to determine their eligibility. People are more likely to enrol into health insurance schemes if they are more likely to use them (referred to as adverse selection in economics literature). This contributory group may also be more proactive in seeking information and treatment, and may also be more aware of the benefits of JKN due to having a higher level of education. Individuals themselves have the best knowledge of whether the benefit of insurance exceeds the cost, which then determines whether or not people decide to get insured (Schneider, 2004; Kahneman, Knetsch and Thaler, 1991). Studies in other settings have also found that knowledge of and trust in the insurance scheme are important factors in predicting enrolment (Kusi et al., 2015; Ozawa and Walker, 2009). Recent evidence from Indonesia reveals that insurance premiums are not the major deterrent, but that patients are more likely to be influenced by the availability of health services and a lack of insurance literacy (Dartanto et al., 2016)

In the case of Indonesia, previous studies have evaluated earlier forms of health insurance using different datasets and techniques, with mixed findings. Johar (2009) evaluated the health cards programme introduced in 2000 and found that it did not increase outpatient utilisation due to the inelastic demand among the recipients.

Hidayat and Pokhrel (2010) analysed the impact of the health insurance programme for civil servants and formal-sector employees and found a positive outpatient utilisation effect especially on private facilities possibly due to supplier-induced demand. Furthermore, Sparrow, Suryahadi and Widyanti (2013) evaluated the health insurance programme for poor people (Askeskin) and found positive utilisation effects on outpatient care. Finally, Vidyattama, Miranti and Resosudarmo (2014) evaluated Askeskin using different datasets and found a positive effect on the likelihood of utilising outpatient care for both conditional and unconditional medical needs.

It appears that most health insurance studies in Indonesia seem to avoid analysing the impact on inpatient care due to the fear of low statistical power associated with inpatient care. In this study, this low power concern does not hinder finding a significant effect. Rather, I show that the impact of JKN was relatively larger on inpatient care compared with outpatient care. Following the Rosenbaum bounds analysis to check the sensitivity of the JKN effect to the dynamic unobserved factors, it also appears that the effect on inpatient care is relatively less sensitive. Since inpatient care is generally more expensive and JKN offers comprehensive benefits, including hospitalisation in both public and contracted private hospitals, an individual is more likely to enrol, particularly if they consider themselves to be a high-risk individual. It can be argued that small sample size may also reduce the likelihood that a statistically significant result reflects a true effect (Button et al., 2013). However, in this study, 1,064 out of 22,708 individuals reported any inpatient visit in any formal health care facilities, thus minimising the concern that the study has too low power in detecting the true treatment effect.





## Chapter 8 Financial protection effect of the JKN programme

### Section 8.1 Introduction

From the general empirical literature discussed in Chapters 4 and 5, I have shown that health insurance in developing countries might be effective in providing adequate financial protection by reducing out-of-pocket (OOP) health expenditure, although the evidence is somewhat mixed. Several systematic reviews have reported a general trend concerning the favourable effects of health insurance on financial protection (Acharya et al., 2013; Giedion et al., 2013; Spaan et al., 2012; Ekman, 2004) but some notable, robust studies showed no statistically significant effect (Raza et al., 2016; Palmer et al., 2015; Camacho and Conover, 2013; Miller, Pinto and Vera-Hernandez, 2013; Nguyen, 2012; Thornton et al., 2010) or even a negative effect, that is, increased OOP health expenditure (Bernal, Carpio and Klein, 2014; Sparrow, Suryahadi and Widyanti, 2013; Wagstaff et al., 2009; Wagstaff and Lindelow, 2008). While health insurance might be expected to increase utilisation of health care services, it may also lead to higher OOP expenditure as well if the insurance does not cover the whole cost of seeking medical treatment, such as transportation costs, drug costs and laboratory costs (Thornton et al., 2010). Insurance that introduces a cost sharing mechanism, such as co-payment and co-insurance has generally offer worse protection than insurance that has no cost sharing. The JKN programme does not have any cost sharing mechanisms and covers quite a comprehensive list of benefits packages. Thus, it is expected to observe reduced OOP health expenditure among its enrolees.

In this chapter, I examine whether the implementation of Indonesia's JKN programme has provided financial protection to its enrolees. The specific objectives are:

- a. To evaluate whether the JKN programme, on average, has any impact on out-of-pocket (OOP) health expenditure at an individual level;

- b. To evaluate whether the JKN programme, on average, has any impact on OOP health expenditure at household level;
- c. To evaluate whether the JKN programme, on average, has any impact on catastrophic health expenditure events at household level; and,
- d. To assess the heterogeneity of the JKN programme effect in terms of locality of residence and by socioeconomic status.

## **Section 8.2 Methodology**

### **8.2.1 Outcome variables (health expenditure)**

Out-of-pocket (OOP) health expenditure data are available for individual and household levels from the IFLS data. The individual level data provide more detailed information on whether the cost was spent on outpatient or inpatient care. All individuals aged 15 years or older were asked whether they had sought any outpatient care in the past 4 weeks and, if they had, the amount of money they had to spend out-of-pocket to pay for medical care. The same questions are available for inpatient care but the time period is longer, 12 months. Furthermore, IFLS data include information on whether the respondent sought self-treatment in the past 4 weeks and the costs incurred, regardless of whether or not they sought care in formal health facilities. This amount of detailed information allows for a more in-depth analysis of the impact of the JKN programme on health expenditure, but it is only available in two waves – 2007 and 2014. To remove the effect of inflation, I adjusted all expenditure values in 2014 using the Indonesian Consumer Price Index (CPI) to 2007 values.

Meanwhile, the household data provide information on medical expenditure for the household over the past 12 months. The respondent for the household survey is the wife of the head of the household, or the female head of the household, or another household member aged 18 years or older who is able to answer the questions. Unlike the expenditure data at individual level, the household data only provide the overall household health expenditure that includes hospitalisation costs, clinic

charges, physician fees, traditional healer fees and medicines. Household data on OOP health expenditure may be useful to control for any intra-household spillover effects (Sparrow, Suryahadi and Widyanti, 2013). Providing one household member with health insurance may relax the budgetary constraint for the entire household, especially if the insured household member is an elderly person or has a history of health problems.

Household data also enables an analysis of catastrophic health expenditure (CHE) which classifies OOP health expenditure as catastrophic if it exceeds a pre-specified fraction of total household consumption (or expenditure). This measure is the official indicator for monitoring UHC financial protection in the Sustainable Development Goals (SDGs indicator 3.8.2), where it is suggested that catastrophic expenditure is defined as 10 percent or 25 percent of total household expenditure. The lower threshold of 10 percent is more relevant for the poor who empirically rarely spend as much as 25 percent of their budget on health care given the need to spend on food and other necessities (Wagstaff et al., 2018).

An alternative definition of CHE is the incidence of health care expenditure equal to or exceeding 40 percent of the household's capacity to pay (Xu et al., 2003). The household's capacity to pay is defined as a household's non-subsistence spending, i.e. a household's consumption expenditure minus subsistence spending. Subsistence spending is the minimum requirement of a household in order to guarantee the most basic standard of living. The average food expenditure of households is used to estimate subsistence spending. To complement the main analysis on individual OOP health expenditure, I also estimate the effect of the JKN programme on household OOP health expenditure and the incidence of catastrophic health expenditure.

### **8.2.2 Treatment and control variables**

As mentioned in the previous chapter, I am interested in the impact of the JKN programme on newly-insured individuals, who were previously uninsured in 2007 but enrolled in the JKN programme in 2014. Two groups of JKN enrollees are

maintained in this analysis: the contributory group who pay the full premium and the subsidised group who get their premium subsidised by the government. Each group is compared to the uninsured group who stayed uninsured in both 2007 and 2014.

I selected independent variables that are likely to modify individual or household health expenditure. They have been chosen to allow estimation the treatment effect of insurance, after controlling for potential confounders that may be related to health expenditure.

- Age

An ageing population is positively related to health care expenditure (Di Matteo, 2005), especially in relation to the elderly population aged 65 years and older who are more likely to utilise long-term care (Mendelson and Schwartz, 1993). However, the effect of age on health expenditure was reported to vary across countries depending on the delivery and financing of health care (O'Connell, 1996). While it is still an open debate as to whether an ageing population contributes to overall per capita health care expenditure, the effect of age on increased individual health care expenditure remains consistent (Zweifel, Felder and Meiers, 1999).

- Gender

Pregnant women are more likely to spend more on health care (for example, prenatal care), but often in developing countries, the decision about seeking care lies with the head of the household (Chirowa, Atwood and Van der Putten, 2013). It is likely that the effect of gender on care seeking behaviour is confounded by women's educational status (Beegle, Frankenberg and Thomas, 2001), where more educated women are likely to have greater independence over their decision to seek care and are, therefore, more likely to spend extra money on health care.

- Education

Health literacy is found to affect medical spending and patients with low health literacy tend to consume an inefficient mix of health care services (Howard, Gazmararian and Parker, 2005; MacLeod et al., 2017). Low general education is one of the strongest predictors associated with inadequate health literacy, regardless of one's health status (Martin et al., 2009).

- Locality of residence (urban/rural)

The split between urban and rural areas reflects differences in economic development, the availability of health care facilities and culture. Since urban areas tend to receive more attention from the government, people living in urban areas can enjoy easier access and a greater choice of medical providers compared with those living in rural areas. Thus, they are more likely to spend greater amounts money on health care. Binary variables for each IFLS province are also included to capture unobserved time-fixed effect that may correlate with the demand and supply of care in the area (Gravelle et al., 2003).

- Wealth index

It is predicted that people with low socioeconomic status will spend more on health care through the utilisation of more expensive health services (Fitzpatrick et al., 2015). In this chapter, I use the asset index to construct wealth quantiles, as previously carried out in chapter 7.

- Medical condition

Individuals suffering from multiple medical conditions are likely to spend more on health expenditure (Vogeli et al., 2007). In this analysis, I used three variables to capture medical condition: the number of acute conditions, the number of chronic conditions and the presence of disability.

### 8.2.3 Estimation model

As previously discussed in Chapter 6, health expenditure can be modelled using a two-part model (2PM) by separating the model into two: the probability of having non-zero health expenditure and the amount spent on health care. However, the 2PM model does not control for any endogenous explanatory variable as it was originally devised to deal with the corner selection problem in health care expenditure. To estimate the causal effect of the JKN programme, I still need to consider the confounding effect of insurance selection bias. This occurs when selection to receive a treatment is correlated with the outcome variables, i.e. OOP health expenditure due to observable or unobservable factors. One of the main arguments of selection bias

usually arises from an individual's health status. An individual with a higher probability of seeking medical treatment in the future will be more likely to enrol in health insurance. In other words, individuals who expect higher health care costs may be more likely to be insured. This phenomenon is widely known in economics literature as adverse selection in health insurance (Cutler and Zeckhauser, 1998), which has been discussed in Chapter 2. Healthy people are expected to consume less health care, hence their decision to stay uninsured.

In the case of JKN, the contributory group are more likely to be subjected to the adverse selection problem because they chose to enrol voluntarily. The subsidised group is arguably less sensitive to the adverse selection issue because they did not have to pay the premium and the decision to enrol did not mainly depend on them but on the eligibility, criteria set by the government. However, evidence suggests that the leakages to non-eligible beneficiaries are a significant problem for public health insurance in Indonesia. In 2010, only 34.6 percent of the poor and near-poor populations reported having subsidised health insurance, whereas only 47.6 percent of the beneficiaries were poor or near-poor (Harimurti et al., 2013). This problem is likely to be driven by the subjectivity of the enrolment process at district level. The selection process can be summarised into two stages: national and district. The first stage is carried out by central government, whereby a quota list of eligible individuals is issued, based on a mixture of geographic and proxy means testing methods. This first stage is arguably exogenous to health care expenditure. The second stage is largely conducted by district-level health staff who identify and enrol eligible households. The decision to enrol eligible households at district level is varied and deploys different methods depending on district-level preferences (Rokx et al., 2009). It is likely that health staff at the district level determine the eligibility criteria based on characteristics other than those prescribed by central government. Nepotism is still a common practice in Indonesia, which implies that individuals who have more connections to health staff at district level are more likely to receive subsidised health insurance/other poverty alleviation programmes.

Because the subsidised public health insurance system, i.e. Jamkesmas, has been integrated into the JKN programme since 2014, it is very likely that its selection problem continues to present bias in terms of the eligibility criteria for receiving the premium subsidy under the JKN programme. To control for the insurance selection bias, I employed the combination of difference-in-difference (DID) and propensity score matching (PSM). Since it is non-parametric by nature, PSM is able to deal with health expenditure data which has a large proportion of zeros.

Equation 8-1

$$\begin{aligned}
 DD^{P, NP} &= E(\Delta y_{it}^P) - E(\Delta y_{it}^{NP}) \\
 &= E(f(\Delta X_{it})) - E(g(\Delta X_{it})) + E(G_{it}) + \Delta\theta_t^P - \Delta\theta_t^{NP} + E(\Delta\varepsilon_{it}^P) - E(\varepsilon_{it}^{NP})
 \end{aligned}$$

If we observe two sets of outcomes –  $y_{it}^P$ , the outcome among the JKN enrollees;  $y_{it}^{NP}$ , the outcome for the uninsured, the difference-in-difference treatment effect of the JKN programme can be obtained by taking the expected difference between the changes among the insured [ $E(\Delta y_{it}^P)$ ] and the uninsured [ $E(\Delta y_{it}^{NP})$ ]. This equation can be solved by functions of observables and unobservables as shown in the second line of Equation 8-1. The first difference in the second line of Equation 8-1, i.e.  $E(f(\Delta X_{it})) - E(g(\Delta X_{it}))$ , represents the differences of changes in outcomes due to the difference in observables. This first difference can be eliminated through matching each treated individual with one or more untreated individuals who are similar in terms of observable variables ( $X_{it}$ ). The treatment effect of the JKN programme on its enrollees is reflected by the  $E(G_{it})$ . The second difference, i.e.  $\Delta\theta_t^P - \Delta\theta_t^{NP}$ , represents the difference of time-specific unobservable factor, common to all individuals in each group, between the treated and the untreated. For example, it can represent the change in economic shock or new legislation that occurs in national level. To eliminate this, we need to assume that the time-fixed unobservable factor for both insured and uninsured change at the same trend.

The propensity score was predicted based on logit regression estimates of the probability of an individual enrolling in the JKN programme in 2014 as a function of



the control variables in 2007. The propensity score for the contributory and subsidised groups was estimated separately. For individual data, the control variables include age, gender, marital status, educational status, asset index as a proxy for socioeconomic status, number of acute conditions, number of chronic conditions, the presence of disability, dummy variables for each province included in IFLS, and sample weights. Kernel matching was chosen as the matching algorithm with a choice of caliper of bandwidth equal to 0.2 of the standard deviation of the logit of the propensity score (Austin, 2011). Standard errors were calculated by bootstrapping to allow for an estimation of the sampling variance of estimated propensity score parameters. DID estimation was calculated by taking the difference between individual health expenditure in 2014 and 2007 and calculating the mean of these differences for each insured and matched uninsured group. These mean differences between the insured and the matched uninsured were tested using a t-test with bootstrapped standard errors.

In this chapter, I also used household data to estimate the effect of the JKN programme on household OOP expenditure. The treatment variable for household analysis is different to the individual analysis. I constructed a binary variable indicating the presence of a household member insured with the JKN programme. Households that were previously covered by any insurance type, including Askes (health insurance for civil servants), Jamsostek (for formal sector employees) and private health insurance, were excluded. Since the treatment variable for household analysis is slightly different to the one used in the individual analysis, i.e. no separate groups between enrolees who paid the premium (the contributory group) and enrolees who received subsidised premiums (the subsidised group), the research question for the household analysis is to establish the effectiveness of the JKN programme on providing financial protection, regardless of the enrolees' ability to pay. Control variables include gender, age, educational status of the head of the household, locality of residence, household size, number of acute conditions affecting daily activities, number of chronic conditions, the presence of any household member who has a disability, a dummy variable indicating utilisation of any type of formal care in the past year, and the dummy variables for each IFLS province.

The fundamental assumption of the DID estimator is that the outcome trends would have been the same in both groups in the absence of the treatment. Depending on the context, there may be several forms of this assumption and different approaches to testing it (Angrist and Pischke, 2009). One way to test this assumption is by calculating the placebo effect of the treatment on the outcome before the programme was implemented. However, the individual OOP health expenditure was not available prior to the IFLS 2007. As the individual data do not permit placebo effect calculation, I used household expenditure data instead to check the parallel trend assumption at household level. It is not unreasonable to assume that the expenditure trend of individuals follows the same pattern as the household health expenditure trend. The parallel trend assumption is likely to be valid if the trend for OOP health expenditure is similar between the insured and the uninsured.

## **Section 8.3 Findings**

### **8.3.1 Individual data**

#### *8.3.1.1 Descriptive summary*

Table 8-1 presents descriptive statistics for OOP health expenditure in 2007 and 2014, comparing the contributory and subsidised groups separately to the uninsured group. All expenditure values in 2014 have been adjusted to 2007 using the Indonesian Consumer Price Index (CPI). All three groups show a general trend of increased expenditure for all three categories, i.e. inpatient, outpatient and self-treatment. This increasing trend is particularly high in inpatient care, especially among the contributory group. This finding is surprising considering that the insured should have been protected from incurring the costs of seeking care. The increasing trend in self-treatment expenditure is also surprising given the insured was expected to rely more on formal health care.

Table 8-1 Descriptive statistics for OOP Health Expenditure in 2007 and 2014, in Indonesian Rupiah (IDR)

Health expenditure by type of care	<b>Uninsured (N = 8,576)</b>	<b>Contributor y (N = 982)</b>	Contributory – Uninsured†	<b>Subsidised (N = 2,503)</b>	Subsidised – Uninsured†
<b>2007</b>					
Inpatient	62,885	90,148	27,263	27,613	-35,272*
Outpatient	8,507	11,386	2,879	9,612	1,105
Self-treatment	6,447	12,589	6,142***	4,424	-2,022
<b>2014</b>					
Inpatient	111,551	254,271	142,720	50,264	-61,287
Outpatient	15,987	18,376	2,389	7,696	-8,291
Self-treatment	20,306	25,737	5,431	14,579	-5,726

† = The mean differences. Significance level: \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

In addition, the contributory group had already spent more OOP health expenditure in formal care (both outpatient and inpatient) and self-treatment in 2007 compared to the other groups, and this group continued to spend more in 2014. The contributory group spent IDR 255,000 out-of-pocket for paying inpatient care, a 180% increase from the spending in 2007. It suggests the presence of selection bias for this group; people who choose to get insured under the JKN programme are likely to demand more health care and spend higher OOP health expenditure than the uninsured people.

Meanwhile, the subsidised group generally spent less than the uninsured group, except for outpatient care in 2007, although the difference is not significant at the 10 percent level. Despite the indication of higher spending among the contributory group and lower spending among the subsidised group compared with the uninsured, the mean difference in health expenditure between the insured and the uninsured is mostly not significant, even at the 10 percent level. This non-significant finding may be explained by a wide confidence interval given the skewed distribution of health care expenditure with a large mass of zero values.

### 8.3.1.2 Naïve estimator for individual health expenditure

Table 8-2 shows the marginal effect of the JKN programme on untransformed OOP health expenditure in 2014 without any other control variables. It follows OLS regression with the following equation:

Equation 8-2

$$Y_i = \alpha + \delta_i T_i + u_i$$

$Y_i$  refers to OOP health expenditure;  $\alpha$  is the model intercept, and  $u_i$  captures random error term.  $T_i$  represents the insurance status with  $T = 1$  as being insured and  $T = 0$  as being uninsured. Thus,  $\delta_i$  can be interpreted as the difference of incurred OOP health expenditure for the insured group compared to the uninsured. The first column for each expenditure category, i.e. outpatient, inpatient and self-treatment, presents the OLS model that includes all samples, whereas the second column only includes individuals with positive expenditure. This table does not demonstrate the causal effect of the JKN programme; it only serves as a comparison with other findings in the following section that utilise a more robust method.

Table 8-2 Regression table of raw/untransformed OOP health expenditure in 2014

OLS	Outpatient [All]	Outpatient [Positive]	Inpatient [All]	Inpatient [Positive]	Self- treatment [All]	Self- treatment [Positive]
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: Treatment variable: JKN Contributory</b>						
Marginal Effect	5,207	75,827	247,326	-2,303,019	2,047	3,386
SE	(10,998)	(84,408)	(208,709)	(5,065,580)	(3,268)	(4,505)
Observations	9,547	1,146	9,549	237	9,549	6,791
<b>Panel B: Treatment variable: JKN Subsidised</b>						
Marginal Effect	-14,899	-100,034	-62,732*	-3,815,540*	-6,662	-9,434
SE	(10,098)	(88,064)	(36,747)	(2,200,130)	(6,789)	(9,159)
Observations	11,067	1,290	11,069	241	11,069	7,913

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

As expected, the JKN contributory group spent higher levels of OOP in outpatient care and self-treatment compared with the uninsured but this increase is not significant. The subsidised group shows lower OOP expenditure for all categories compared with the uninsured. Only the effect on inpatient care is significant at the 10 percent level.

On average, people in the subsidised group spend IDR 15,000, IDR 62,000 and IDR 6,600 less on outpatient, inpatient and self-treatment costs respectively, compared with the uninsured.

Table 8-3 presents the marginal effect of the JKN programme on three categories of OOP health expenditure costs according to a two-part model (2PM) approach. The first part models zeros in OOP health expenditure, which is typically handled using a model for the probability of a positive outcome:

*Equation 8-3*

$$\varphi(Y > 0) = \Pr(Y > 0|X) = F(X\delta)$$

Where X is a vector of control variables,  $\delta$  is the corresponding vector of parameters to be estimated, and F is the cumulative distribution function of an independent identically distributed error term, typically solved by either logit or probit model (Belotti et al., 2015). The second part handles positive OOP expenditures, which is usually represented as:

*Equation 8-4*

$$\varphi(Y|Y > 0, X) = G(X\gamma)$$

Where X is a vector of control variables,  $\gamma$  is the corresponding vector of parameters to be estimated, and G is an appropriate density function for  $Y|Y > 0$ . In this analysis, the first part used a probit model to estimate the probability of incurring positive OOP expenditure, while the second part used GLM regression based on a Gamma distribution with the log link function to model the positive OOP expenditure.

According to Table 8-3, there is no significant effect on outpatient OOP expenditure for the contributory group. Meanwhile, the contributory group is 2 percent more likely to have positive expenditure, and out of those who spend positive expenditure, the contributory group spend IDR 168,000 more than the uninsured group. However, only the first part is significant at the 1 percent level. Finally, the JKN programme decreases the probability of incurring positive self-treatment costs among the contributory group but does not have much effect on the actual self-treatment cost.

Table 8-3 Regression table of the two-part model analysis on OOP health expenditure in 2014

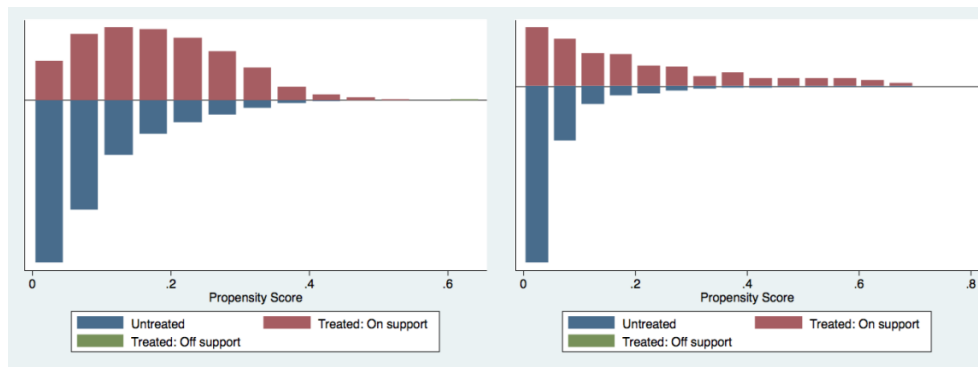
	Outpatient OOP		Inpatient OOP		Self-treatment	
	First part	Second part	First part	Second part	First part	Second part
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: Treatment variable: JKN Contributory</b>						
Marginal Effect	0.00	7,569	0.02***	167,658	-0.03*	1,380
SE	(0.01)	(6,536.00)	(0.00)	(69,404.32)	(0.02)	(1,962.36)
<b>Panel B: Treatment variable: JKN Subsidised</b>						
Marginal Effect	-0.02**	-5,288	0.00	-53,799	0.01	-3,987
SE	(0.01)	(5,055.42)	(0.00)	(41,161.55)	(0.01)	(2,840.71)

Significance level \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

According to panel B in Table 8-3, the subsidised group is two percent less likely to incur OOP expenditure for outpatient care but there is no significant effect on the actual cost. The JKN programme also decreases the actual cost of inpatient care and self-treatment for the subsidised group, but neither of these is significant at even the 10 percent level.

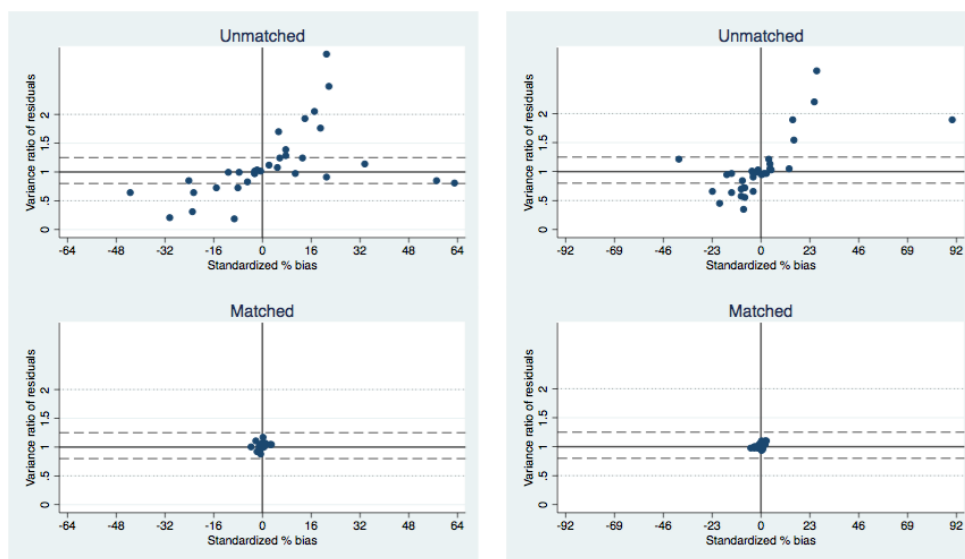
Overall, it is suggested that the JKN programme increases the OOP expenditure for the contributory group but decreases the OOP expenditure for the subsidised group. However, none of these effects on the positive expenditure are significant at the 10 percent level. The two-part model can solve the skewed distribution of health expenditure data, but it is unable to control for the insurance selection bias. Next, I will present the findings from the PSM-DID analysis, which is more robust in controlling for insurance selection bias.

### 8.3.1.3 PSM-DID analysis



(a)

(b)



(c)

(d)

(a) shows support between the treated and untreated for the contributory group, whereas (b) shows this for the subsidised group.

(c) and (d) show the reduced bias before and after matching for the contributory and subsidised groups respectively.

*Figure 8-1 Support and balance after propensity score matching*

Figure 8-1a and 8-1b show histograms of the propensity scores after matching using kernel matching. Despite its left-skewed distribution, there are ample overlaps between the treated and the control group. This suggests that the matching process has successfully retained adequate samples to avoid attrition bias from the cases of off-support. Figures 8-1c and 8-1d show the extent to which matching has reduced

the bias in this analysis. Both graphs demonstrate that after matching, the standardised percentage of bias across covariates has been reduced to near zero.

The estimated treatment effect, based on Equation 8-1, are presented in Table 8-4, with the contributory group results in panel A and the subsidised group in panel B. Column (1) reports the estimates from a PSM analysis for outpatient OOP expenditure. PSM enables us to estimate the average treatment effect on treated (ATT) on the assumption that the control variables have no explanatory power over outcome variables after matching. Overall, the result shows that there is no significant effect for both the contributory and subsidised groups, a pattern similar to the findings in the two-part model in Table 8-3.

Table 8-4 Results of the PSM-DID analysis of the impact of the JKN programme on OOP health expenditure

	Outpatient OOP		Inpatient OOP		Self-treatment	
	PSM (1)	PSM-DID (2)	PSM (3)	PSM-DID (4)	PSM (5)	PSM-DID (6)
<b>Panel A: Treatment variable: JKN Contributory</b>						
ATT	6,818	8,417	240,365	154,914	6,714	-1,583
SE	(13,497)	(9,819)	(176,500)	(124,647)	(6,715)	(6,274)
<b>Panel B: Treatment variable: JKN Subsidised</b>						
ATT	-10,395	-11,082	-14,198	2,202	-5,464	-1,697
SE	(8,803)	(9,214)	(77,273)	(55,876)	(5,933)	(3,405)

The treated group was matched with the control group through kernel Epanechnikov with bandwidth 0.01. The reported standard errors in parentheses were calculated by bootstrapping with 200 replications. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

While PSM only controls for observable selection bias, PSM-DID can further control for fixed unobservable selection bias. Based on Table 8-4, no estimate of PSM-DID reports a significant effect, even at 10% level. The expansion of JKN to the previously uninsured population has no statistically significant effect on reducing or increasing OOP health expenditure. Stratifying the DID-PSM estimates by asset index quintiles and urban/rural area still results in no significant impact for both the contributory and subsidised groups (see

Table 8-5).

Table 8-5 Impact of JKN on health care spending, by asset index quintiles (Q1 = poorest; Q5 = richest) and urban/rural area

	Inpatient OOP	Outpatient OOP	Self-treatment
JKN Contributory			
Q1	63,710 (59,011)	-10,549 (8,281)	-2,141 (12,519)



Q2	25,845 (68,540)	3,803 (25,901)	1,495 (7,740)
Q3	66,901 (120,311)	33,451 (41,285)	-2,408 (2,374)
Q4	352,129 (328,393)	-679 (15,235)	1,780 (2,448)
Q5	168,895 (303,598)	3,011 (7,728)	-3,037 (14,485)
Urban	222,083 (186,934)	14,206 (11,605)	-1,438 (8,113)
Rural	-9,442 (50,927)	-2,464 (9,763)	-1,854 (4,587)
<hr/>			
JKN Subsidised			
Q1	17,763 (56,258)	-1,859 (7,930)	-5,708 (10,437)
Q2	-31,166 (29,168)	-23,406 (26,080)	-5,113 (7,580)
Q3	-23,912 (85,775)	-31,639 (32,825)	-1,962 (1,516)
Q4	53,842 (44,288)	433 (9,678)	11,751 (13,713)
Q5	-14,045 (264,320)	11,916 (8,932)	1,903 (3,196)
Urban	-29,175 (126,450)	-12,660 (17,127)	95 (1,990)
Rural	21,411 (43,192)	-10,029 (9,843)	-3,110 (5,335)

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

### 8.3.2 Household data

In this sub-section, I present the analysis of the effect of the JKN programme at household level. I only have one treatment group because it is possible to have two individuals belonging to different types of JKN membership, i.e. the contributory and subsidised schemes. This happens because the JKN membership for non-salaried individuals is not at the household level and one household can have more than one family (either related or unrelated), especially in rural areas or the slums.

Nevertheless, this is still an important policy question because even when only one member of the household is enrolled in the insurance scheme, this can ease the burden on the household's overall expenditure. The interpretation of the treatment effect therefore needs to be understood as a joint effect of JKN programme. From this

point, an insured household is defined as a household which has at least one member enrolled in the JKN programme.

#### 8.3.2.1 Descriptive summary

Table 8-6 presents the descriptive statistics for both the outcome and the control variables. On average, the insured households were more likely to live in an urban area, have the head of household who only finished primary education, have bigger household size, report more acute conditions affecting daily activities, utilise more health care, and come from lower socioeconomic status compared to the uninsured households.

Looking at the amount of OOP health expenditure, the insured household spent, on average, IDR 9,600 less than the uninsured household in the baseline year and this difference is significant at the 1 percent level. However, the insured increased their spending in 2014 to almost the same level as the uninsured, thereby closing the gap between the insured and the uninsured.

Turning to the catastrophic health expenditure (CHE) measures, the insured households had a lower incidence of CHE in 2007 compared with the uninsured and these differences are significant at a 5 percent level for two out of three CHE indicators. Aligned with my observation on the amount of OOP health expenditure spent, the differences between the CHE indicators are no longer significant in 2014.

Table 8-6 Descriptive statistics of IFLS household data, 2007–2014

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2007	2014
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Variables	Uninsured (N=3,720)	JKN insured (N=2,027)	Mean difference	Uninsured (N=3,720)	JKN insured (N=2,027)	Mean difference
<b>Outcome variables</b>						
OOP health expenditure†	42,073	32,426	-9,646***	54,826	55,070	243
OOP/total expenditure > 10%	4.20%	3.40%	-0.80%	4.70%	5.10%	0.50%
OOP/total expenditure > 25%	1.30%	0.70%	-0.6%**	1.00%	1.10%	0.10%
OOP/non-food expenditure > 40%	3.90%	2.80%	-1.1%**	3.80%	4.00%	0.20%
<b>Control variables</b>						
Gender of the head of household	68.40%	69.70%	1.30%	68.40%	69.70%	1.30%
Urban/Rural	44.30%	49.90%	5.6%***	44.30%	49.90%	5.6%***
Age of the head of household	41.17	40.78	-0.39	47.68	47.28	-0.40
Educational level of the head of household						
Primary	45.70%	49.50%	3.8%***	44.50%	48.90%	4.4%***
Secondary	40.80%	38.80%	-2.00%	41.20%	38.80%	-2.4%*
University	5.60%	4.70%	-0.90%	6.90%	5.60%	-1.3%*
Household size	3.81	4.09	0.27***	3.78	4.13	0.35***
Number of acute conditions affecting daily activities	2.12	2.20	0.08*	3.36	3.64	0.28***
Number of chronic conditions	0.17	0.15	-0.02*	0.34	0.34	0.00
Any disability	1.60%	2.30%	0.7%*	15.60%	16.40%	0.80%
Any utilisation (outpatient or inpatient in the past year)	25.10%	27.50%	2.4%**	29.60%	38.20%	8.6***
Total household expenditure†	1,800,000	1,653,000	-147,112***	2,497,000	2,326,000	-170,610***

Significance level \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

### 8.3.2.2 Impact estimates

Table 8-7 displays the estimated effect of the JKN programme on the actual health expenditure for households. The first column presents the cross-sectional regression on untransformed health expenditure in 2014, controlling for demographic characteristics, educational status, total household expenditure, the presence of medical conditions and the use of any type of formal health care. The OLS model is based on:

Equation 8-5

$$Y_i = \alpha + \delta_i T_i + \sum_{j=1}^J \beta_j X_{ij} + u_i$$

Where Y refers to OOP health expenditure;  $X_{ij}$  includes all control variables described above and  $\beta_{ij}$  is the coefficient for each  $X_{ij}$ ;  $\alpha$  is the model intercept, and  $u_i$  captures random error term. I found that JKN insured households on average spend IDR 2,600 more than uninsured households, a relatively small difference, but this effect is not significant at 10 percent level. In the second column, the log of health expenditure is used instead, which is then re-transformed to the actual cost again by applying the Duan smearing approach. The effect becomes smaller, but it is still not significant.

Table 8-7 The estimated effect of the JKN programme on household OOP health expenditure

OLS untransformed (1)	OLS with Log and Duan smearing (2)	Two-part model (3)	PSM (4)	DID-PSM (5)
OOP Health Expenditure				
2,648 (6,606)	909 (2,941)	3,513 (5,740)	2,375 (6,728)	9,207* (5,467)

Significance level \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

The third column presents the findings from the two-part model that considers the skewed distribution of health expenditure, following similar approach to Equation 8-3 and Equation 8-4. The effect of the JKN programme is still not significant, with only a slightly bigger magnitude compared to the first and second columns. The fourth column shows a PSM analysis on cross-sectional data (2014) and demonstrates a similar effect to the first column, though still not significant. Finally, the fifth column shows the mean differences between OOP in 2014 and 2007 after matching, following similar approach to Equation 8-1. While the magnitude of the JKN effect is larger than in the first column, this finding is only significant at the 10 percent level. The finding from the PSM-DID model agrees with my observation on the descriptive statistics. Despite having lower health expenditure compared to the uninsured in 2007, the insured households increased their health expenditure to the same level of the uninsured in 2014. Cross-sectional analysis in column 1-4 may not be able to detect this increased expenditure over time.

Table 8-8 shows the estimated effect of the JKN programme on CHE indicators. The first row demonstrates the proportion of households which have OOP health expenditure at more than 10 percent of total household expenditure, whereas the second row shows the same proportion with a higher threshold, 25 percent. The first column shows the calculation of the effect of the JKN programme on CHE indicators using the OLS model, whereas the second column uses probit modelling as all CHE indicators are binary outcomes. Nevertheless, both models display very similar findings. The third column shows the findings from the PSM-DID analysis, representing a much larger effect compared with the OLS and probit models. The insured households are 1.26 percent more likely to experience CHE if the threshold is set to 10 percent, but this effect is not significant at 10 percent level. Changing the threshold to 25 percent reduces the magnitude but the effect is still not statistically significant. Using the ratio of OOP expenditure and non-food expenditure with 40% threshold (see the third row), the effect is rather similar to the first row. Overall, there is not enough evidence to claim that the JKN programme affects the incidence of CHE.

*Table 8-8 The estimated effect of the JKN programme on catastrophic health expenditure (CHE) incidence (in %)*

CHE	OLS	Probit (Marginal Effect)	PSM-DID
OOP/HH>10%	0.25 (0.68)	0.25 (0.68)	1.26 (0.82)
OOP/HH>25%	-0.02 (0.30)	-0.02 (0.30)	0.65 (0.40)
OOP/NFOOD>40%	0.12 (0.64)	0.12 (0.64)	1.19 (0.75)

*HH = total household expenditure; NFOOD = Non-food household expenditure*

*Standard errors in parentheses. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01*

Table 8-9 presents the estimated effect of the JKN programme on OOP health expenditure and CHE indicators stratified by socioeconomic quintiles and locality of residence area. While no apparent increasing or decreasing trend from the lowest to the highest quintile can be observed, the effect of JKN becomes significant for those in

the third and fourth quintiles, showing the opposite signs. While the insured households in the third quintile spent IDR 17,000 **less** compared to the uninsured households, the insured households in the fourth quintile spent IDR 37,000 **more** than the uninsured households. This pattern is also evident for all three incidences of CHE, but the effect is more significant for the fourth quintile. The insured households in the fourth quintile are 6.2 percent more likely to have health expenditure exceeding 10 percent of total household expenditure, and 5.6 percent more likely to have health expenditure exceeding 40 percent of non-food expenditure compared with the uninsured in the same quintile.

Table 8-9 The impact of JKN on OOP health expenditure (in IDR) and CHE incidence (in %) stratified by socioeconomic status quintile and urban/rural area

	OOP (in IDR)	OOP/HH>10%	OOP/HH>25%	OOP/NFOOD>40%
Q1	-3,062 (6,919)	0.165 (1.916)	-0.533 (0.008)	0.836 (0.019)
Q2	6,553 (6,935)	0.659 (1.662)	1.083 (0.008)	1.444 (0.016)
Q3	-17,422** (8,727)	-3.489* (1.826)	-0.144 (0.010)	-3.092* (0.017)
Q4	37,109*** (12,571)	6.242*** (1.965)	2.706*** (0.010)	5.598*** (0.017)
Q5	21,179 (21,273)	3.374 (2.092)	0.027 (0.010)	1.860 (0.019)
Urban	19,471** (9,722)	2.361* (1.236)	1.873*** (0.006)	2.520** (0.011)
Rural	-2,732 (6,186)	-0.189 (1.120)	-0.379 (0.005)	-0.119 (0.011)

HH = total household expenditure; NFOOD = Non-food household expenditure

Standard errors in parentheses. \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

In addition, the JKN effect on OOP health expenditure and three CHE indicators is more prominent in urban areas compared with rural ones. The insured households living in urban area spent IDR 19,500 more than the uninsured households in urban area. The insured households are also more likely to experience catastrophic health expenditure compared to the uninsured households.

To check the parallel trend assumption, I plotted the OOP health expenditure from 2000 to 2014 with price adjustment to 2007 level. It is assumed that the trend of OOP health expenditure in both the insured and uninsured groups is similar before the introduction of the JKN programme in 2014, which will be reflected in the 2000 and 2007 data. According to Figure 8-2, it is likely that the parallel trend assumption can be upheld.

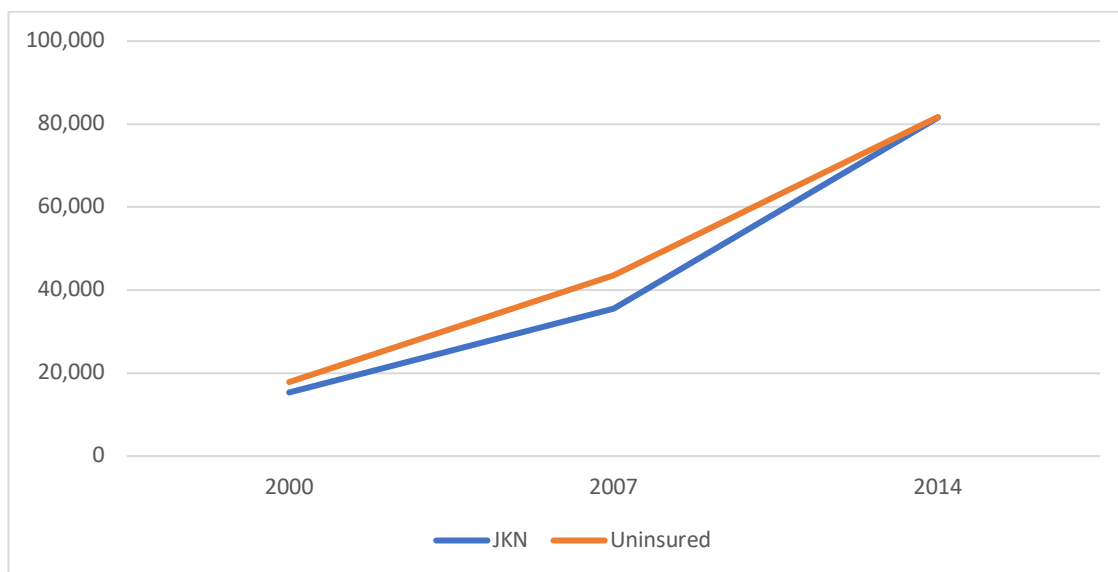


Figure 8-2 Parallel trend for OOP health expenditure (in IDR), 2000–2014

### 8.3.3 Positive expenditures

Even though it is not significant, the positive coefficients on the OOP health expenditure is unexpected given the generosity of JKN programme. If people spent more OOP health spending, the purpose of the spent costs is still not clear considering JKN did not collect any co-insurance or deductible costs at the point of treatment.

Without the intention to draw causal effect, descriptive information from patients who sought care in IFLS 2014 data might shed some light in explaining limited effect of the JKN programme on OOP health expenditure. This data was not utilised into my empirical model as it is only available for 2014. From a more detail questionnaire

regarding medical expenditure from the last visit to outpatient facilities, 5,695 people sought outpatient care in 2014. It is found that 642 out of 1873 (34 percent) individuals who were insured under the JKN programme, excluding civil servants and formal sector employees, used JKN benefits to pay for the outpatient care. Among 642 individuals who used JKN benefits to seek care, 607 paid nothing for prescription and 35 people paid on average IDR 340,000 (GBP 17.5) for prescription. Furthermore, 581 people out of 642 patients paid nothing for treatment care and the other 61 people paid on average IDR 270,000 (GBP 14).

Data on OOP expenditure on the last visits for inpatient care showed almost similar pattern. From 1480 individuals who sought inpatient care in 2014, 607 reported to be enrolled in JKN programme. Out of 607, 419 patients (69 percent) used JKN benefit to seek care, a much higher rate compared to the utilisation of JKN benefit to outpatient care. Among those 419 patients, 332 paid zero expenditure for prescription and 96 paid on average IDR 1 million (GBP 51). In addition, 271 out of 419 patients paid zero for treatment care and 148 paid on average IDR 2,3 million (GBP 117). These numbers have considered the amount of OOP expenditure that were reimbursed by the insurance. This descriptive finding agrees with findings from a qualitative survey in Indonesia, albeit a much lower rate, which reported that 31 percent of 422 individuals who were insured by the JKN programme still had to spend out-of-pocket when they sought care in hospitals and 10 percent paid out-of-pocket in primary care clinics (Thabrany and Abidin, 2017).

It can also be observed that some patients still had to spend money even though they received care under the JKN programme. Not only for prescription costs which has been documented as the common source of extra payment for the insured (Thornton et al., 2010), but also treatment costs that are meant to be covered completely under JKN programme. The amount of average OOP prescription and treatment costs are also substantial as the average minimum national wages in 2014 was only IDR 1,6 million (Range: IDR 910,000 – IDR 2,2 million) (BPS Indonesia, 2017a). It means, on average, JKN insured patients may spend 20% of their income to pay for prescription after using outpatient care or 62.5% for inpatient care. In addition to OOP



prescription costs, JKN insured patients may have to spend another 17% of their income for treatment fees in outpatient clinics or 143% for hospitals fee.

## Section 8.4 Discussion

In this chapter, I have found that individuals in the JKN contributory group increased their OOP health spending, even though this finding was not significant at even the 10 percent level after controlling for time-invariant unobservable selection bias.

Meanwhile, the JKN subsidised group also increased their OOP health spending but to a lesser magnitude compared with the impact on the contributory group; this finding was also not significant at the 10 percent level. Furthermore, I found that there is no significant effect on OOP health expenditure and catastrophic health expenditure events among the insured households, on average. However, there is an indication that the increased spending due to JKN is only limited to insured households in quintile 4, who are also more likely to live in an urban area. The seemingly stronger evidence at household level compared to the individual level might be due to the larger sample size at household level; the treatment indicator for the household analysis combines the presence of both the contributory and the subsidised groups.

This limited finding may be correlated with the finding in the previous chapter about the JKN effect on increased utilisation among the contributory and subsidised groups. No reduction in OOP health spending may still be considered an improvement in the sense that JKN did not increase OOP spending despite an increase in utilisation. If people could not access care and had zero expenditure before the introduction of JKN, then having increased utilisation but no increase in OOP health expenditure after enrolling in the insurance means that JKN still has a protective effect. Another scenario for no JKN effect relates to when people did not seek care before the treatment period, and still had not sought care after the treatment period, hence their zero spending.

In this study, I have found that the expansion of the JKN programme has not reduced the level of OOP health expenditure for the enrollees who sought medical care. Further research is needed to understand the reasons for the increased expenditure. Considering the benefits of the programme, another empirical question relates to whether this increased expenditure results in improved health status. The next

chapter discusses my attempt to find evidence about the effects of health insurance on improving health status.

# Chapter 9 The impact on blood pressure and hypertension rate

## Section 9.1 Introduction

In the previous two chapters, I have estimated the impact of the Indonesian public health insurance (*Jaminan Kesehatan Nasional – JKN*) programme on the level of utilisation of health care and the out-of-pocket (OOP) health expenditures at the individual level. While the JKN programme appears to encourage use of health care services, it has also increased OOP health expenditures. In this chapter, I evaluate the impact of JKN programme on health status. The health insurance effect on blood pressure was chosen for this study because hypertension is the leading risk factor for adult mortality in many developing countries (Lim et al., 2013), including Indonesia. Hypertension is the primary risk factor for the top two causes of death in Indonesia: stroke (21% of all deaths) and ischaemic heart disease (9% of all deaths) (World Health Organization, 2010). IFLS survey has collected blood pressure measurement since 2000 and history of chronic diseases, including hypertension, since 2007. Another reason for choosing this outcome is that blood pressure management may be modified by health care utilisation which can be influenced by insurance. Health insurance reduces the cost of access to medical providers which may encourage the enrolees to initiate blood pressure management with regular anti-hypertensive medication. The enrolees are also more likely to maintain good adherence to treatment which is an important factor for adequate blood pressure control (Menanga et al., 2016).

In this chapter, the specific objectives are:

- e. Evaluate whether JKN programme, on average, has reduced blood pressure level among its enrolees compared to the uninsured
- f. Evaluate whether JKN programme decreases the prevalence of hypertension among its enrolees compared to the uninsured
- g. Evaluate whether JKN programme has improved the management of hypertension by measuring the rate of patient awareness of the condition, treatment, and control of hypertension.

- h. Assess the potential effect of rurality and socioeconomic status on the effect of JKN programme effect on hypertension outcome.

## Section 9.2 Conceptual framework

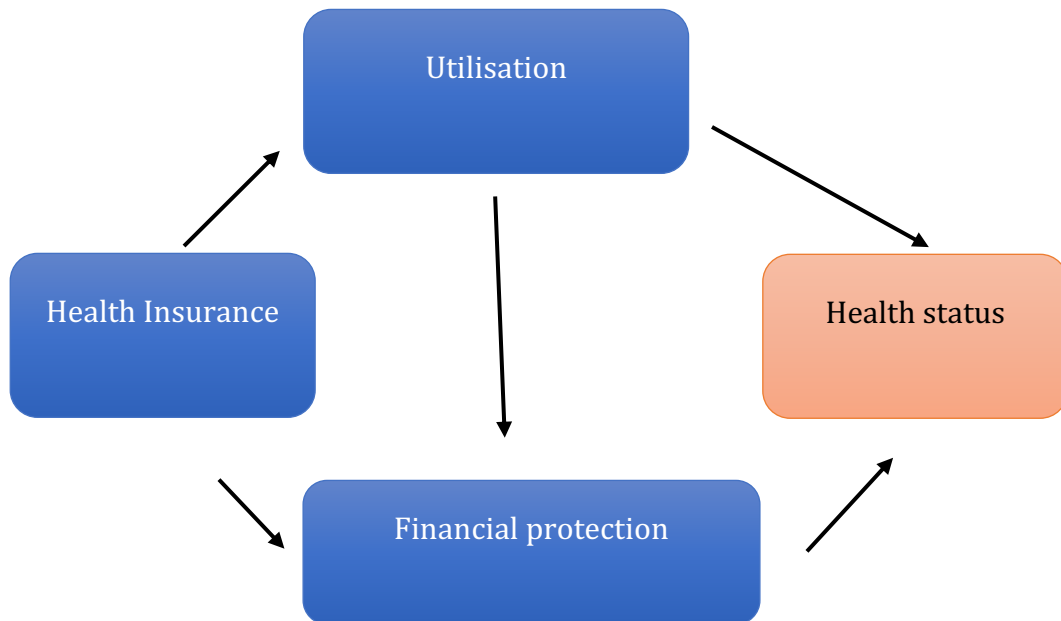


Figure 9-1 Conceptual model of the relationships between health insurance and health status

Source: (Ross and Mirowsky, 2000; Grossman, 2000)

Figure 9-1 provides a conceptual model to predict the relationship between health insurance and health status. The model predicts three paths on how health insurance can improve individual's health. The top path suggests that health insurance influences the quantity of health care services. Through changes in medical care consumption, an individual may stay healthy and free from illness and avoid deterioration in health (Grossman, 1972). The model explicitly suggests changes in medical care should happen first before the effect of health insurance on health can be realised. Health insurance can act as a subsidy on health care prices and based on economic theory reduced price should increase demand of medical care (Folland, Goodman and Stano, 2014). Based on this first theory, use of medical care is an act of investment to sustain the health stock from both natural (i.e., aging) and external deteriorations (i.e., illness) (Grossman, 2000).

Based on early evidence from the US experience (Ross and Mirowsky, 2000), it is argued that increased access to medical care due to health insurance may not necessarily contribute to better health outcomes. They found that private insurance had no association with better outcomes and public insurance led to worse outcomes even after adjusting for socioeconomic status. However, having medical insurance greatly reduced both the likelihood of not having the money to purchase necessary medical services and the likelihood of not having money to pay bills and buy necessities, or commonly called catastrophic financial effect. This suggestion translates to a second path of how health insurance influences health outcomes. While health insurance may or may not increase utilisation of health care, the effect of health insurance on health outcomes can come indirectly through its financial protection effect (Ross and Mirowsky, 2000). Health insurance enables an individual to sustain their optimum living condition by protecting their wealth from any excessive medical bills. With sustained living conditions, that individual is protecting their health stock from any deterioration that may come from non-optimum living conditions. For example, an insured individual can potentially avoid large bills for private health care which would in turn reduce the catastrophic impact of health financing, thus reducing the impact on food consumption and other necessary expenses. Reduced food consumption may mean choosing less-healthy food consumption or sub-optimal food consumption and both may affect physical health.

In addition, living with huge medical debt may reduce one's well-being by impaired mental health, such as depression or anxiety (Hojman, Miranda, and Ruiz-Tagle, 2016; Keese and Schmitz, 2014) and even physical health, such as diastolic blood pressure (Sweet et al. 2013). A cross-country evidence from 17 European countries suggests that long-term debt can be associated with poorer health outcome (Clayton, Liñares-Zegana, and Wilson, 2015). The consequence of financial debt on psychological well-being may also depend on different coping mechanisms used by individuals which further suggests a wide range of heterogeneity of the debt effect (Bridges and Disney, 2010). Nevertheless, the evidence suggests that financial protection from health insurance may contribute to improved individual's health status.

## Section 9.3 Methodology

### 9.3.1 Outcome variables

The outcome variables in this chapter are mainly derived from blood pressure measurement and history of diagnosed hypertension (HT) which are available in IFLS 2007 and 2014. An Omron meter, HEM-7203 was used for taking blood pressure of all household members age 15 or older. Respondents were measured three times on alternate arms for blood pressure and the average of systolic and diastolic from three measurements were taken and then dichotomised using the WHO definition of hypertension, i.e. Systolic >140 mmHg and/or Diastolic >90 mmHg (Whitworth and World Health Organization, International Society of Hypertension Writing Group, 2003). The blood pressure measurements were taken on the same respondents allowing a panel data analysis. A scatterplot of measured blood pressure over the years suggests an increasing trend (Figure 9-2). Judging by the histogram of measured blood pressure in Figure 9-3, both systolic and diastolic are normally distributed with slight skew to the right.

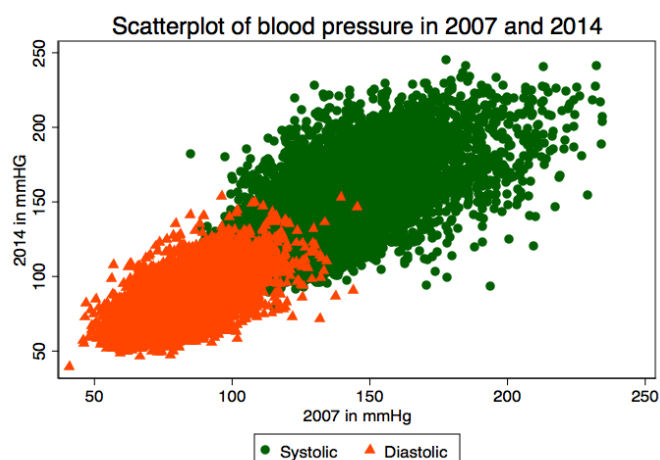


Figure 9-2 Scatterplot of measured systolic and diastolic

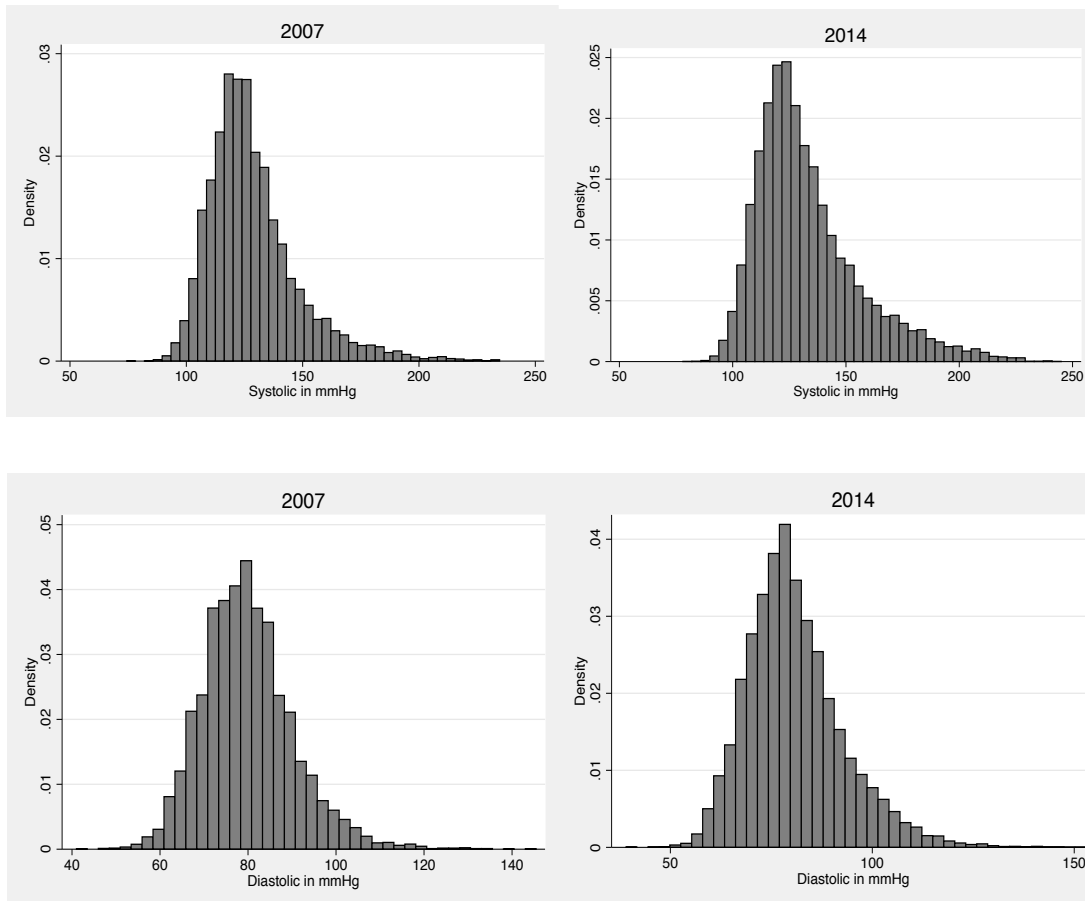


Figure 9-3 Histogram of systolic and diastolic, by year

The next step is to determine the proportion of individuals who had hypertension. In many studies, individuals were called being hypertensive if their blood pressure (BP) measurement was either  $\geq 140$ mmHg Systolic Blood Pressure (SBP) or  $\geq 90$ mmHg Diastolic Blood Pressure (DBP) **OR** if they were taking medication to lower blood pressure (Burt et al., 1995; Morenoff et al., 2007; Pereira et al., 2009; Joffres et al., 2013; Hertz et al., 2005; Falaschetti et al., 2014; Lloyd-Sherlock et al., 2014). Another definition of being hypertensive is any individual who had  $\geq 140$ mmHg SBP or  $\geq 90$ mmHg DBP **OR** self-reported of hypertension diagnosis by any health professional (Duru et al., 2007; Witoelar, Strauss and Sikoki, 2012; Strauss et al., 2010). This identification process is commonly used in health and retirement study (HRS)-type data to calculate levels of hypertension because only individuals who self-reported to have hypertension were given the follow up question on hypertension treatment. This implies that no individual took anti-hypertensive medication without being aware of having HT, which is a reasonable assumption. Because IFLS questionnaires



were developed closely similar to HRS type data (Strauss, Witoelar and Sikoki, 2016), I chose the second approach to calculate the prevalence of HT.

Awareness, treatment, and control of hypertension were defined using commonly recognised standards (Joffres et al., 2013). Awareness of hypertension was self-reported and was based on previous diagnosis of hypertension by a medical professional. In the survey questionnaire, this information was recorded using the following question: *Has a doctor/paramedic/nurse /midwife ever told you that you had hypertension?* Those answering 'yes' were subsequently asked: *"In order to manage your hypertension are you currently taking prescribed medication on a weekly basis?"* Those answering yes to this question were considered to be on treatment. In those reporting to be on antihypertensive medication, control of hypertension was defined as having a mean SBP<140 and DBP <90 mmHg.

Using three criteria related to hypertension (i.e. blood pressure measurement, self-reported hypertension diagnosis, and an indicator for taking anti-hypertensive medication), six groups of individuals can be identified from our sample. Figure 3a – 3c depicts the detail of those six groups in both years. The first is a group of individuals who had elevated blood pressure but was unaware of their situation. Their number increased from 3,598 to 4,049 individuals. The second group is a group of individuals who was aware of their hypertensive condition, still had elevated blood pressure, and were not taking anti-hypertensive medication at the time of the survey, whereas the third group is almost similar to the second group, but these respondents took anti-hypertensive medication. Both groups increased in size over time, but the second group increased more significantly from 352 in 2007 to 1,429 in 2014. Meanwhile, the fourth group consists of individuals who were aware of their hypertensive condition but had normal blood pressure and took anti-hypertensive medication (i.e. their hypertension was under control due to medication). The fifth group was similar to the fourth group (i.e. they were aware of their hypertension because of diagnosis in the past) but did not take anti-hypertensive medication (i.e. their blood pressure was under control without medication). While the fourth group did not change much (257 in 2007 and 229 in 2014), the fifth group increased from

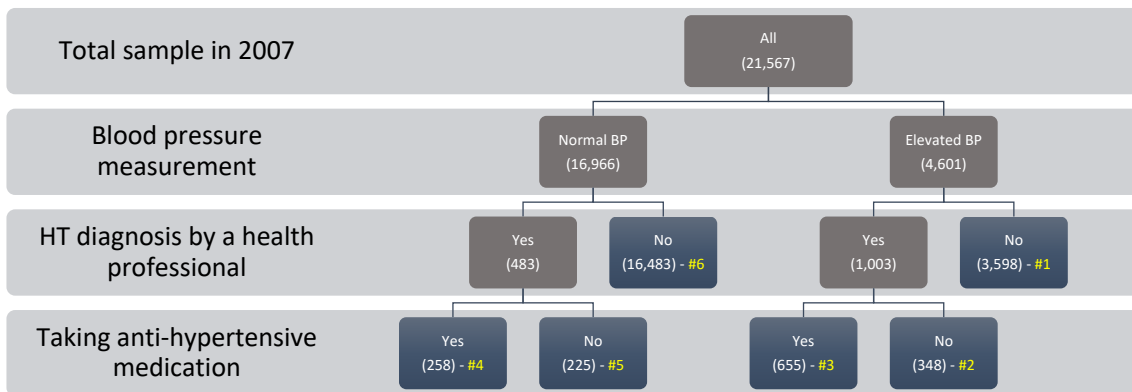
226 to 901 in 2014. This may have happened because of lifestyle changes, such as weight loss, that may have helped reduce blood pressure. Finally, the sixth group, which is the largest among the others, consists of non-hypertensive people.

Based on those six groups in Figure 3, we could construct the formula to calculate the prevalence of hypertension, awareness, treatment, and controlled.

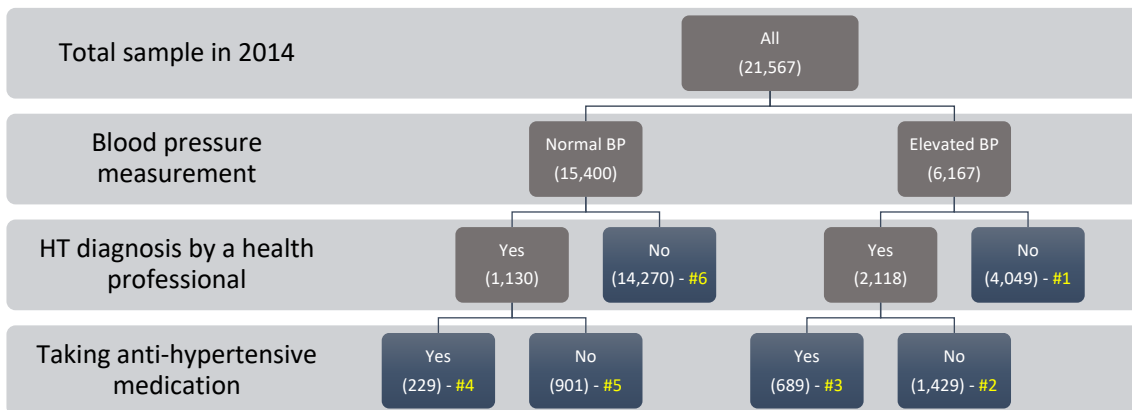
$$\text{Hypertension} = \frac{\#1+\#2+\#3+\#4+\#5}{\text{total sample}} \quad \text{Treatment} = \frac{\#3+\#4}{\#1+\#2+\#3+\#4+\#5}$$

$$\text{Awareness} = \frac{\#2+\#3+\#4+\#5}{\#1+\#2+\#3+\#4+\#5} \quad \text{Controlled} = \frac{\#4}{\#3+\#4}$$

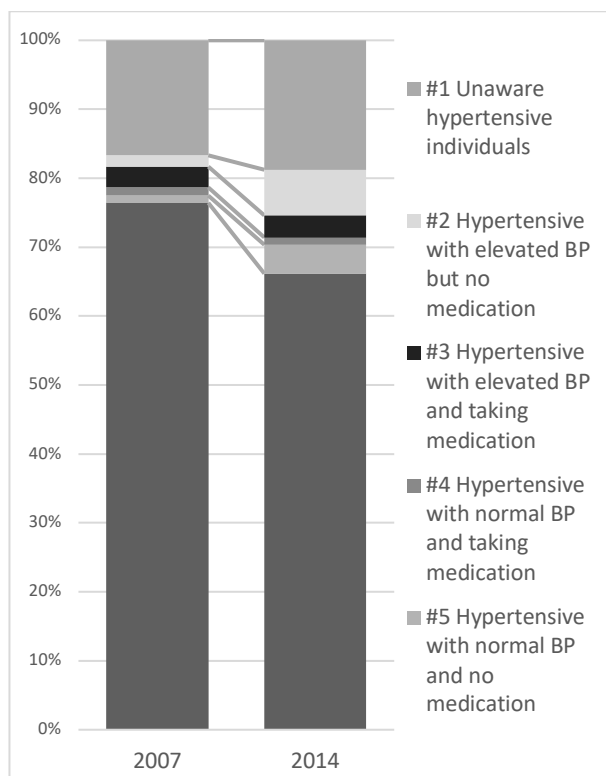
Prevalence is calculated as the sum of all groups who had hypertension, either through elevated blood pressure or self-reported hypertension diagnosis, divided by the total sample. For the purpose of this analysis, the numerator of the prevalence can be named as hypertensive individuals. Awareness is calculated as the total number of hypertensive individuals who were aware of their condition divided by the total number of hypertensive individuals. Treatment is calculated as the sum of hypertensive individuals receiving anti-hypertensive medication divided by the total number of hypertensive individuals. Controlled is calculated as the number of individuals who had anti-hypertensive medication and had normal blood pressure divided by the total number of individuals who received anti-hypertensive medication.



(a)



(b)



(c)

Figure 9-4 Summary of hypertension measurement in IFLS 2007 and 2014

### 9.3.2 Independent variables

I selected independent variables that are likely to modify blood pressure or known to be risk factors of cardiovascular disease (CVD). They are chosen to allow estimation the treatment effect of insurance after controlling for potential confounders that may be related to hypertension-based outcome. For instance, if age is correlated with HT and is unequally distributed in the insured and uninsured groups, then the estimate of treatment effect of insurance will be biased. These variables can be categorised into two groups: biomedical characteristics (age, gender, body mass index, smoking status, physical activities, and history of diabetes mellitus) and socioeconomic status (living in urban/rural area, education status, and wealth index). I also included dummies for each IFLS provinces that will capture province-specific factors such as culture, geography and local policy.

#### *Biomedical characteristics*

- Age

Prevalence of hypertension increases with age (Sun, 2015). One mechanism by which the prevalence of hypertension is increased in relation to aging may be advancing endothelial dysfunction associated with aging through an increase in oxidative stress. In addition, endothelial cell deterioration is also involved in aging-related endothelial dysfunction (AlGhatrif et al., 2013). Population studies also demonstrated the increased prevalence of hypertension among older population in Indonesia (Hussain et al., 2016).

- Gender

In general, women have higher prevalence, awareness, treatment, and control of HT across all races in the USA (Cutler et al., 2008). By contrast, in Indonesia, men are more likely to have higher prevalence but still higher awareness and control of HT (Hussain et al. 2016). Indonesian women were more likely to have hypertension when they are older but men had higher prevalence when they were younger (<45 years) (Christiani et al., 2016).

- Body mass index

Body mass index (BMI) is defined as weight (in kg) divided by height (in meter) squared. Height was measured with Shorr measuring boards and weight was measured using Seca floor-model scales developed in collaboration with UNICEF. We used World Health Organization (WHO) standards which defines adults whose BMI is under 18.5 are considered underweight, those whose BMI is under 16 are considered severe underweight, those whose BMI is 25 or greater are overweight, and those whose BMI is 30 or greater are considered obese. Obesity has been associated with elevated hypertension, diabetes, and other cardiovascular disease (Gaal, Mertens and Block, 2006; Mokdad et al., 2003; Rahmouni et al., 2005).

- Smoking status

Cigarette smoking has been shown to cause damage on human's vascular system and modulate contributing to increased risk of fatal cardiovascular outcomes (Messner and Bernhard, 2014). In a global study of smoking prevalence and cigarette consumption 1980-2012, Indonesia has seen a slight increase in smoking prevalence from 29.2 % (95%CI: 27.3 – 29.8) in 1980 to 30.1% (95% CI: 28.9 – 31.4), and a bigger increase in mean daily consumption per smoker from 8.9 (95% CI: 7.8 – 10.1) to 11 (95% CI: 10.1 – 11.9) (Ng et al., 2014).

- Physical activity

Physical activity was assessed through a set of questions [modified short form of International Physical Activity Questionnaire (IPAQ)] on the types and times of physical activities engaged in, in all parts of life: work, home and exercise. The total duration of activities was transformed to Metabolic Equivalent of Tasks (METs)-minutes and summed to gain an overall estimate of physical activity in a week and further classified as low, moderate and high level of physical activity (Di Blasio, Di Donato and Mazzocco, 2016).

- History of Diabetes

Insulin resistance causes diabetes mellitus and hypertension. People with diabetes mellitus are more likely to have hypertension and uncontrolled blood pressure (DeFronzo and Ferrannini, 1991). However, a population study in Indonesia did not find a strong relationship between diabetes and hypertension (Rahajeng and Tuminah, 2009).

#### *Socioeconomic status*

- Locality of residence

The split between urban and rural area reflects the difference in the economic development, the availability of health care facilities, and cultural practices. As urban area tends to receive more attention from the government, people living in urban area can enjoy easier access and more choices of medical provider compared to in rural area. It is expected to see higher rate of awareness and treatment in the urban area. However, people living in rural area may have healthier diet as fast food chains are less available in the village, which in turn may contribute to lower prevalence rate of hypertension. In Indonesia, the prevalence of hypertension was significantly higher in urban (49.8%) compared with rural (46.4%) areas (Hussain et al. 2016).

- Education

Education may play an indirect role in hypertension by the means of health behaviour. More educated people are more likely to adopt healthy behaviours, such as eating healthier diet. On the other hand, a person with lower education is more likely to work in an occupation requiring manual labour, which may increase their physical activity, while a person with higher education is more likely to work in an office, leading to a more sedentary lifestyle. In Indonesia, education was a significant factor in women ( $p < 0.05$ ) to be associated with lower odds of uncontrolled hypertension among those who were under 45 years old (Christiani et al., 2016). One epidemiology study of hypertension in Indonesia found that people who did not finish elementary school had higher odds of being hypertensive than those who finished elementary school (Rahajeng and Tuminah, 2009). Among Indonesian male

adults age 40 or higher, the prevalence of hypertension progressively rose across levels of education. However, after adjusting for sociodemographic variables, including current smoking and level of physical activity, the odds of hypertension did not vary significantly across level of education or wealth index in either men or women (Hussain et al., 2016). While in theory education may affect the level of blood pressure, but education may also be influential in modifying healthy behaviour which has more direct impact on blood pressure.

- Wealth index

Socioeconomic status may affect the level of blood pressure, but its mechanism is not clear. Poor people may have less access to healthier diet, but rich people are more likely to live a more sedentary lifestyle. However, it is thought socioeconomic status may play a bigger role in the access to medical providers and to preventative care. Based on an epidemiology study in Indonesia, socioeconomic status has no association with prevalence of HT, but this may be related to awareness, treatment, and control (Rahajeng and Tuminah, 2009). Hypertension can often be asymptomatic which leads to the detection/preventive care issue. A poor person with no health insurance is less likely to undergo blood pressure screening, whereas an insured poor person with asymptomatic hypertension is likely to go for preventive care visits, get diagnosed early, initiate the hypertensive treatment, and maintain a good treatment compliance. In this chapter, I used the asset index to construct wealth quantiles as I had done in the previous two chapters.

### 9.3.3 Estimation model

#### *Difference-in-Differences (DID) with regression*

I begin by estimating conventional parametric DID models for the outcomes. Consider the following equation:

*Equation 9-1*

$$Y_{it} = \beta_0 + \beta_1 T_t + \beta_2 D_{it} + \beta_3 T_t \times D_{it} + X_{it} \theta + \phi_s + \varepsilon_{it}$$

where  $Y_{it}$  stands for the outcome variables for individual  $i$  in year  $t$ . The year dummy  $T_t$  captures aggregate factors that would cause changes in outcome variables even in the absence of a policy change.  $D_{it}$  is the treatment group dummy that captures possible differences between the treatment and control groups prior to the introduction of JKN programme in 2014.  $T_t \times D_{it}$  is the interaction between the year and the treatment dummy which is the regressor of interest: it gives us the causal reform effect, provided the assumptions required in the DID approach are satisfied. State dummies,  $\phi_s$ , account for permanent differences across the 13 Indonesian provinces.  $X_{it}$  contains 1 x K column vector of control variables. As usual,  $\varepsilon_{it}$  stands for unobserved heterogeneity and is assumed to be normally distributed with zero mean.

DID is usually estimated by ordinary least squares and the treatment effect is easily identifiable from the sign and statistical significance of  $\beta_3$  in Equation 1. Binary outcomes can also be estimated with DID using nonlinear model, such as probit or logit model. However, the treatment effect, unlike in the linear model, is not equal to the interaction term and it cannot be constant across the treated population because the expectation of the outcome variables is bounded between zero and one. It has been shown that the treatment effect in nonlinear DID is the cross difference of the conditional expectation of the *observed* outcome minus the cross difference of the conditional expectation of the *counterfactual* outcome (Puhani, 2012). The sign of the treatment effect in any strictly monotonic transformation model, such as logit, probit, and tobit, is the same as the sign of the coefficient of the interaction term (Puhani, 2012; Karaca-Mandic, Norton and Dowd, 2012). Since all outcomes in this analysis are binary, I estimated all regression models using both OLS and logit to compare the consistency of any observed findings.

Because of serial correlation in panel data, conventional DID standard errors may understate the standard deviation of the estimated treatment effects, leading to serious overestimation of  $t$ -statistics and significance levels (Bertrand, Duflo and Mullainathan, 2004). A simple method to correct this serial correlation issue is by clustering over the individuals to obtain cluster-robust standard errors.



Difference-in-differences assumes that outcome trends are similar between the insured and uninsured groups before the intervention and that the only factors explaining changes in outcomes between the two groups are constant over time. It implies that the outcomes would have moved in parallel trend between the insured and uninsured groups in the absence of the programme. A falsification test requiring two rounds of data available before the start of the programme can verify whether any difference in trends appears between the two groups before the implementation of the programme. By plotting the mean of outcome variables for each year between the insured and uninsured, we can physically observe any trend difference prior to the reform. I run placebo regression assuming counterfactually that the JKN programme took place in a different year. Should the coefficient of interest be significant in a non-reform year, the common time trend assumption would be seriously challenged (Lechner, 2010; Ziebarth and Karlsson, 2014).

#### *PSM and DID approach*

As in Chapter 7 and 8, I also estimated the treatment effect of JKN programme using the combination of propensity score matching (PSM) and difference-in-difference (DID). The most attractive feature of propensity score matching compared to regression type estimators is its nonparametric nature as PSM assumes a flexible functional form to estimate the outcome model (Rosenbaum and Rubin, 1983). While PSM controls for any observed confounders, DID removes the time constant confounders. The PSM-DID approach follows the following equation:

*Equation 9-2*

$$\begin{aligned}
 DD^{P,NP} &= E(\Delta y_{it}^P) - E(\Delta y_{it}^{NP}) \\
 &= E(f(\Delta X_{it})) - E(g(\Delta X_{it})) + E(G_{i1}) + \Delta\theta_t^P - \Delta\theta_t^{NP} + E(\Delta\varepsilon_{it}^P) - E(\varepsilon_{it}^{NP})
 \end{aligned}$$

If we observe two sets of outcomes –  $y_{it}^P$ , the outcome among the JKN enrollees;  $y_{it}^{NP}$ , the outcome for the uninsured, the difference-in-difference treatment effect of the JKN programme can be obtained by taking the expected difference between the changes among the insured [ $E(\Delta y_{it}^P)$ ] and the uninsured [ $E(\Delta y_{it}^{NP})$ ]. This equation can be solved by functions of observables and unobservables as shown in the second

line of Equation 8-1. The first difference in the second line of Equation 9-2, i.e.  $E(f(\Delta X_{it})) - E(g(\Delta X_{it}))$ , represents the differences of changes in outcomes due to the difference in observables. This first difference can be eliminated through matching each treated individual with one or more untreated individuals who are similar in terms of observable variables ( $X_{it}$ ). The treatment effect of the JKN programme on its enrollees is reflected by the  $E(G_{it})$ . The second difference, i.e.  $\Delta\theta_t^P - \Delta\theta_t^{NP}$ , represents the difference of time-specific unobservable factor, common to all individuals in each group, between the treated and the untreated. For example, it can represent the change in economic shock or new legislation that occurs in national level. To eliminate this, we need to assume that the time-fixed unobservable factor for both insured and uninsured change at the same trend.

The propensity score was predicted based on logit regression estimates of the probability of an individual enrolling in the JKN programme in 2014 as a function of the control variables in 2007. The propensity score for each voluntary and subsidised group were estimated separately. The use of covariates from 2007 instead of from 2014 was chosen to minimise a reverse causality issue. In addition, I included the sample weight accounting both complex survey design and attrition rate into our propensity score estimation (DuGoff, Schuler, and Stuart, 2014). Based on the coefficient estimates from the logit model, I constructed a propensity score that allowed us to quantify the distance between each of the treated and untreated cases in the sample. This propensity score is essentially the predicted probability of being in the treated (insured) group. I applied the common support rule that observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls are excluded. I also excluded the treated cases for which a sufficiently close match could not be found among the controls, and it was determined by choice of bandwidth or caliper, as described below.

In this analysis, I used nearest neighbour matching in which we matched each treated case with the five 'nearest' untreated cases. In addition to matching each treated case with the five nearest untreated cases, I also set the maximum distance of propensity score between the treated and non-treated case with a pre-defined caliper 0.01. As

robustness check, I also used kernel matching as an alternative matching technique. In kernel matching, each insured individual is given a weight of one. A weighted composite of comparison observations is used to create a match for each insured individual, where uninsured individuals are weighted by their distance in propensity score from insured individuals within a range, or bandwidth, of the propensity score. Only observations outside the range of common support are discarded. Kernel matching maximizes precision (by retaining sample size) without worsening bias (by giving greater weight to better matches) (Garrido et al., 2014).

## **Section 9.4 Findings**

This section presents the result of the impact evaluation of JKN programme on hypertension. Before presenting the regression results, the descriptive results are presented first.

### **9.4.1 Descriptive statistics**

Table 9-1 shows the summary of hypertension-related variables in percentages. Both SBP and DBP shows an increasing trend from 2007 to 2014 for all groups. Consequently, the prevalence also shows an increasing trend. The contributory group has the lowest prevalence in both years compared to the other groups but its growth rate is almost 50% higher in 2014 compared to the 2007 figure.

Over time, people with elevated BP were more likely to be aware of their hypertensive condition and this is true for all groups. Although the uninsured showed the highest awareness in 2007, it became the lowest rate in 2014. Meanwhile, the awareness for the contributory group increased almost twofold in 2014. However, the treatment rates show a mixed pattern. While the contributory group shows an increasing trend, the rates for both subsidised and uninsured groups show a decreasing pattern, substantially more for the latter group. While the uninsured showed decreased treatment rate followed by decreased control rate of hypertension

as well, the subsidised group had higher control rate despite its decreased treatment rate. Overall, the contributory group showed a more positive pattern such that more people were aware of their hypertension, received treatment, and had better control of hypertension in 2014 compared to 2007

Table 9-1 Descriptive table of hypertension rates, by year and insurance status

	Uninsured		Contributory		Subsidised	
	2007	2014	2007	2014	2007	2014
SBP (in mmHg)	127.045	131.817	124.573	128.814	127.015	131.807
DBP (in mmHg)	79.081	80.364	78.829	79.851	78.891	80.184
Prevalence* (in %)	24.4	34.4	21.3	30.6	24	34.5
Awareness^ (in %)	28.8	41.2	27.6	51.8	25.6	41.4
Treatment† (in %)	17.5	10.8	15.1	18.1	15.8	8.5
Controlled‡ (in %)	29.1	21.2	27.6	30	26.4	31

\*Prevalence: The union of elevated blood pressure (Systolic/Diastolic > 140/90 mmHg) and self-reported of hypertension diagnosis/total sample. ^Awareness: Hypertensive individuals who were aware of their condition/hypertensive individuals  
 †Treatment: Hypertensive individuals who took medication to lower their blood pressure/hypertensive individuals ‡Control: Hypertensive individuals with normal BP and taking medication/hypertensive individuals who took medication

Table 9 2 presents a summary of the descriptive statistics for control variables used in the analysis. The contributory group is more likely to be female and younger, have higher BMI, live in urban area, come from the richest population, be highly educated, be a non-smoker, and have been diagnosed diabetes mellitus by a health professional. On the other hand, the subsidised group is more likely to be older, come from the poorest population and have no education. Both the subsidised and uninsured are more likely to be a smoker than the contributory group. Table 9-3 shows that this prediction is correct that the richest has the highest awareness and treatment rate while the poorest has the lowest one. This pattern also persists from 2007 to 2014 suggesting that this inequality has already existed prior to the introduction of JKN programme in 2014. However, the controlled rate which presents the success of blood pressure management shows a pro-poor pattern in 2007, i.e. the first and second quintiles had higher controlled rate than richer quintiles; however, the poorest quintile had a large drop in controlled level in 2014 making it similar to the richest quintile.

Table 9-3 presents the distribution of systolic and diastolic across year, wealth quintiles, and rural/urban area. Systolic and diastolic in all quintiles show an increasing trend and the difference between the poorest and the richest appears small clinically. Awareness and treatment rate imply access to health care facilities. Based on the finding of the JKN programme effect on utilisation of health care in the previous chapter, it is predicted to observe higher awareness and treatment rate among the richest quintile.

Table 9-2 Descriptive table of control variables, by year and insurance status

Control variables	Uninsured		Contributory		Subsidised	
	2007	2014	2007	2014	2007	2014
<b>Age (years)</b>	37.19	43.71	33.8	40.33	37.34	43.82
18-29 year	37.50%	18.40%	44.60%	22.10%	35.10%	16.10%
30-39 year	22.80%	27.70%	25.90%	32.50%	26.30%	28.80%
40-49 year	18.50%	20.60%	16.50%	21.80%	18.40%	23.20%
50-59 year	12.30%	17.20%	7.90%	13.60%	10.70%	16.10%
60-69 year	6.40%	9.40%	3.90%	6.80%	7.10%	9.10%
≥ 70 year	2.50%	6.70%	1.20%	3.20%	2.40%	6.70%
<b>Marital status</b>						
Single	18.90%	8.70%	24.40%	9.50%	14.70%	6.10%
Married	72.50%	78.50%	71.90%	82.20%	77.30%	81.70%
Previously-married	8.60%	12.80%	3.70%	8.40%	8.00%	12.30%
<b>Male</b>	45.70%	45.70%	42.10%	42.10%	44.90%	44.90%
<b>Urban</b>	41.20%	47.30%	71.20%	73.90%	40.80%	51.90%
<b>Wealth quintiles</b>						
Quintile 1 (the poorest)	18.40%	19.10%	7.30%	9.00%	30.70%	28.60%
Q2	20.40%	20.20%	13.10%	15.80%	27.60%	25.70%
Q3	21.20%	21.50%	22.40%	22.70%	20.40%	20.40%
Q4	21.50%	21.70%	27.20%	22.00%	13.70%	16.40%
Quintile 5 (the richest)	18.40%	17.50%	29.90%	30.50%	7.60%	8.80%
<b>Education status</b>						
No education	9.30%	8.50%	3.10%	2.30%	9.90%	9.30%
Primary education	41.10%	40.50%	21.60%	21.00%	50.10%	49.40%
Secondary	44.80%	43.30%	61.40%	59.20%	38.40%	38.00%
Higher	4.80%	7.50%	14.00%	17.50%	1.60%	3.20%
<b>BMI (kg/m<sup>2</sup>)</b>	22.33	23.57	22.95	24.39	21.89	22.99
Underweight	14.70%	10.30%	12.50%	8.90%	16.40%	12.40%
Normal BMI	63.40%	55.60%	59.10%	48.00%	64.40%	58.20%
Overweight	21.90%	33.40%	28.40%	42.80%	19.10%	28.60%
Obese	4.40%	8.00%	6.20%	11.40%	2.80%	6.10%
<b>History of Diabetes</b>	0.70%	2.30%	1.30%	4.10%	0.20%	2.00%

### Smoking status

Non-smoker	64.50%	60.80%	70.70%	67.60%	63.60%	60.20%
Ex-smoker	2.10%	5.20%	2.00%	5.30%	1.80%	4.80%
Light (1-10 cig/day)	10.40%	10.20%	10.90%	9.00%	11.80%	10.30%
Medium (11-20)	19.10%	18.20%	13.10%	14.90%	19.70%	20.10%
Heavy (>20)	3.80%	5.70%	3.30%	3.30%	3.20%	4.50%

### Physical activity

Low	22.00%	40.50%	30.30%	47.90%	20.20%	36.50%
Moderate	33.20%	24.50%	32.40%	24.50%	30.40%	24.20%
High	44.80%	30.40%	37.40%	23.80%	49.40%	35.00%

Table 9-3 shows that this prediction is correct that the richest has the highest awareness and treatment rate while the poorest has the lowest one. This pattern also persists from 2007 to 2014 suggesting that this inequality has already existed prior to the introduction of JKN programme in 2014. However, the controlled rate which presents the success of blood pressure management shows a pro-poor pattern in 2007, i.e. the first and second quintiles had higher controlled rate than richer quintiles; however, the poorest quintile had a large drop in controlled level in 2014 making it similar to the richest quintile.

Table 9-3 Blood pressure and hypertension rate in 2007 and 2014 across wealth quintiles and urban/rural area, all three groups (contributory, subsidised, and uninsured)

	Systolic (mmHg)		Diastolic (mmHg)		Prevalence*		Awareness <sup>^</sup>		Treatment <sup>†</sup>		Controlled <sup>††</sup>	
	2007	2014	2007	2014	2007	2014	2007	2014	2007	2014	2007	2014
Q1 (Poorest)	127.7	133.5	78.5	79.9	23.8	35.2	23.5	38.2	14.8%	8.6%	34.0	26.0
Q2	127.1	131.6	78.6	80.0	23.6	33.9	28.6	42.2	17.5%	11.0	32.2	32.9
Q3	125.7	131.0	78.9	80.4	22.1	34.3	29.7	44.7	17.5%	11.6	28.8	23.2
Q4	125.9	130.2	79.2	80.5	23.3	32.7	30.5	48.2	19.3%	15.2	20.5	17.7
Q5 (Richest)	126.0	129.5	80.2	80.6	25.0	33.1	33.5	49.4	20.5%	16.5	27.9	26.5
Rural	127.0	131.4	78.8	79.9	23.6	33.2	26.5	42.4	16.3%	10.7	28.6	26.0
Urban	126.0	130.8	79.4	80.6	23.5	34.3	31.9	46.1	19.7%	13.9	27.9	24.4
Total	127.2	131.1	79.1	80.3	23.6	33.8	29.2	44.5	18.0%	12.6	28.3	24.9

\*Prevalence: The union of elevated blood pressure (Systolic/Diastolic > 140/90 mmHg) and self-reported of hypertension diagnosis/total sample

<sup>^</sup>Awareness: Hypertensive individuals who were aware of their condition/hypertensive individuals

<sup>†</sup>Treatment: Hypertensive individuals who took medication to lower their blood pressure/hypertensive individuals

<sup>††</sup>Control: Hypertensive individuals with normal BP and taking medication/hypertensive individuals who took medication

#### 9.4.2 Results from the difference-in-differences (DID) estimator

Table 9-4 presents the DID estimates of the JKN programme effect on blood pressure, both systolic and diastolic, with or without controlling for potential confounders. Columns (1) – (6) represent the comparison between the contributory group and the uninsured whereas columns (7) – (12) present the model comparing the subsidised and the uninsured group. Columns (1), (4), (7), and (10) show the DID estimation without adjusting for control variables. Enrolling in JKN programme does not show any significant effect in both systolic and diastolic among the contributory group, nor the subsidised group. While it is discouraging to observe no direct impact on blood pressure, it is not surprising considering the JKN programme had only been running for a maximum of 9 months. Columns (2), (5), (8), and (11) present the DID estimation for systolic and diastolic with the addition of control variables which should improve the precision of any observed impact. As expected, no significant change was observed after controlling for control variables. We did not observe changes in any estimates after adding physical activity as a control.

Table 9-5 presents the adjusted and unadjusted estimation of JKN on prevalence, awareness, treatment, and control of hypertension. Panel 1 shows the effect on the contributory group while the subsidised group is represented in panel 2. Column (1), (4), (7), and (10) show the unadjusted estimates. The JKN programme seems to have significant effect in increasing awareness, treatment, and control of hypertension among the contributory group. Among the contributory enrolees who were diagnosed hypertension by medical providers or had elevated blood pressure, 12% (95% CI: 2.2% - 21.8%) were more likely to be aware of their hypertension compared to the uninsured. Those contributory enrolees were also 10% (95% CI:

4.12% - 15.9%) more likely to receive anti-hypertensive medication compared to the uninsured.

The evidence of JKN programme effect among the subsidised group is very limited. Compared to the uninsured, the subsidised group who had elevated blood pressure were 3% (95% CI: -2.9% - 8.8%) more likely to be diagnosed for their hypertensive condition, and those who received anti-hypertensive treatment were 13% (95% CI: -2.7% - 28.7%) more likely to have controlled blood pressure, but neither of those effects are significant even at 10% level. Columns (2), (5), (8), and (11) presents the adjusted prevalence, awareness, treatment, and control of hypertension, taking into account the control variables and dummies for provinces. The effect of JKN on prevalence of hypertension was not statistically significant for either the contributory or subsidised groups. After adjusting for the control variables, the effect of JKN on the awareness among the contributory group decreased to 9% (95% CI: 1.2% - 16.8%) from 12%, but the effect on treatment increased to 11% (95% CI: 3.2% - 18.8%) from 10% in the unadjusted estimates. Even after adjusting for both biological and socioeconomic factors, the effect of JKN on controlled hypertension was still not statistically significant. Meanwhile no changes in outcome variables were observed among the subsidised group in panel 2, with the exception of hypertension control, which increased to 14% (95% CI: 6.8% - 20.8%) and was significant at the 5% level.

Columns (3), (6), (9), and (11) presents DID estimation with one additional control variable: physical activity. While the addition of physical activity did not change the estimation of JKN effect on both systolic and diastolic, it seems to have modified the JKN effect on control rate of hypertension among the contributory group. It is estimated that the contributory enrollees who received anti-hypertension treatment were 19% (95% CI: -0.6% - 38.6%) more likely to have controlled blood pressure compared to the uninsured, but that effect was significant only at the 10% level.



Table 9-6 shows a similar analysis compared to Table 5, but uses a logit model to estimate the JKN effect on prevalence, awareness, treatment, and control of hypertension. Overall, there was no marked difference between results from the OLS and logit models. It is encouraging to see the consistency of the findings from both the OLS and logit models.

#### **9.4.3 Results from the difference-in-differences (DID) estimator with propensity score matching (PSM)**

*Next, I re-analysed the JKN effect on hypertension by combining propensity score matching and DID. First, I estimated the propensity score of the likelihood for an individual to enrol in the JKN programme. To do this, I ran a logit model of treatment indicator on all control variables including physical activities and sampling weight. Only control variables from pre-programme period (i.e. 2007) were used in the propensity score model.*

*Table 9-7 presents the treatment effect of JKN using PSM-DID approach. I compared the results from two different matching techniques: Nearest neighbour matching and kernel matching. Both techniques were able to reduce the bias based on pre-treatment baseline to almost zero as shown in Figure 4. Overall results from Table 7 showed similar pattern with the findings from DID alone. JKN had no significant effect on reducing blood pressure or the prevalence of hypertension, but JKN may have some positive effect on increasing awareness and treatment rate*

significantly among the contributory group compared to the uninsured. The main difference between findings from the PSM-DID (

Table 9-7) and DID-only (

Table 9-5 and

Table 9-6) estimators was that the JKN effect on hypertension control was much bigger and statistically significant at 5% level using PSM-DID. Using this method, the contributory group showed 42% higher control rate of hypertension compared to the uninsured.

#### 9.4.4 Heterogeneity of the JKN effect

The next step is to investigate whether the JKN effect varied by wealth. Findings from the chapter 7 suggest that the JKN effect on increased utilisation for the contributory group was stronger among the richest and the JKN effect for the subsidised group was more prominent among the poorest. One way to explore this is to interact the treatment variable, year fixed effect, and the wealth dummy variables, which would enable us to calculate the difference between the JKN effect on the poorest and the richest. I created a new variable which equals to one if an individual was in the poorest quintiles (quintiles 1 and 2) and zero otherwise. I also checked the heterogeneity of JKN effect based on urban/rural locality to check whether the JKN effect favours individuals living in more developed region (i.e., urban areas) using OLS. These results are presented in Table 9-8. Panel A shows results comparing urban and rural areas, whereas Panel B shows comparison between the poorest and the richest groups.

### *Panel A: Urban vs rural comparison*

*From Table 9-8, panel A, the data suggest that JKN contributory has stronger effect of reducing systolic in rural areas compared to the JKN contributory enrolees in urban areas, despite no overall effect of JKN shown previously in*

Table 9-7. No differences were observed on diastolic blood pressure or prevalence of hypertension, consistent with the overall no effect previously shown. At the same time, the JKN effect on increasing awareness of hypertension was 21% higher in urban areas compared to rural areas. While the JKN effect on treatment and control rate of hypertension were also stronger in urban area, these differences were not significant at the 10% level.

The heterogeneity of JKN effect among the subsidised group showed a more favourable picture than the overall effect. The JKN effect on awareness of hypertension in rural areas was positive and statistically significant at the 1% level. By contrast, the effect of JKN on awareness was negative in urban areas. Similarly, the JKN effect on control of hypertension was also positive and significant in rural areas, but negative in urban areas. Subsidised enrolees living in rural areas were 29% more likely to have better control of their hypertension compared to the uninsured living in rural area after JKN. Since people living in poverty were the target group for the subsidies, and a high proportion of poor people live in rural areas, this finding suggests that the subsidies reached the target population.

### *Panel B: Richest vs. poorest comparison*

Similar to the urban/rural comparison, the finding from Table 9-8, panel B suggests a heterogeneity of JKN effects between the poorest and the richest. In this comparison, the JKN effects were positive and statistically significant on increased awareness, treatment, and control among the richest enrolled in the contributory group. Meanwhile, poor people enrolled in the JKN subsidised scheme seems to have 1.86 mmHg (p-value < 0.01) higher diastolic compared to rich people in the subsidised

group. No differences were observed for blood pressure and prevalence of hypertension.

Table 9-4 Effect of the JKN programme on blood pressure (Outcome variables: Systolic and Diastolic in mmHg)

	Contributory vs Uninsured						Subsidised vs Uninsured					
	Systolic			Diastolic			Systolic			Diastolic		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DID effect	-0.57 (0.60)	0.38 (0.61)	0.56 (0.60)	-0.07 (0.38)	0.14 (0.40)	0.28 (0.39)	-0.14 (0.42)	-0.53 (0.44)	-0.18 (0.43)	0.12 (0.25)	0.01 (0.26)	0.21 (0.26)
Control variables	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Health behaviour	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Observations	18102	18099	18031	18102	18078	18031	21112	21109	21023	21112	21109	21023

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ ; standard errors are in parentheses. Standard error is clustered at the individual level. All models are estimated by OLS. Number of observations reduce slightly for every model that controls for physical activities because 4% individuals in 2014 did not report physical activities questionnaires. Control variables include age groups, marital status, gender, education, wealth index in quintiles, rural/urban, regional dummies, and history of diabetes. Health behaviour includes BMI, smoking status, and physical activities. All estimates are adjusted by sampling weight taking into account both attrition rate and survey sampling design. The first column for each systolic and diastolic sub-group (i.e. column 1, 4, 7, and 10) shows the treatment effect without any control variables. The second column (i.e. 2, 5, 8, and 11) includes control variables as stated previously and the third column (i.e. 3, 6, 9, and 12) includes physical activities as an additional control variable.

Table 9-5 Effect of the JKN programme on prevalence, awareness, treatment, and control of hypertension (OLS estimation)

OLS	Prevalence#			Awareness^			Treatment†			Controlled††		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel 1 JKN Contributory												
DID effect	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	0.12** (0.05)	0.09** (0.04)	0.10** (0.04)	0.10*** (0.03)	0.11*** (0.04)	0.09*** (0.03)	0.10 (0.11)	0.13 (0.10)	0.18* (0.11)
Observations	18,102	18,100	18,030	5,260	5,260	5,218	5,260	5,260	5,218	726	726	717
Panel 2 JKN Subsidised												
DID effect	0.01 (0.01)	-0.00 (0.01)	-0.00 (0.01)	0.03 (0.03)	0.03 (0.03)	0.02 (0.03)	-0.01 (0.02)	-0.03 (0.02)	-0.03 (0.02)	0.13 (0.08)	0.14** (0.07)	0.13* (0.07)
Observations	21,110	21,110	21,022	6,200	6,200	6,148	6,200	6,200	6,148	810	810	800
Control variables	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Physical activities	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

#Prevalence: The union of elevated blood pressure (Systolic/Diastolic > 140/90 mmHg) and self-reported of hypertension diagnosis/total sample

^Awareness: Hypertensive individuals who were aware of their condition/hypertensive individuals

†Treatment: Hypertensive individuals who took medication to lower their blood pressure/hypertensive individuals

††Control: Hypertensive individuals with normal BP and taking medication/hypertensive individuals who took medication

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01; standard errors are in parentheses. Standard error is clustered at the individual level. All models are estimated by OLS. All estimates can be seen as a percentage change. Control group for both panels are the uninsured group. Number of observations reduce slightly for every model that controls for physical activities because 4% individuals in 2014 did not report physical activities questionnaires. Control variables include age groups, marital status, gender, education, wealth index in quintiles, rural/urban, regional dummies, and history of diabetes. Health behaviour includes BMI, smoking status, and physical activities. All estimates are adjusted by sampling weight taking into account both attrition rate and survey sampling design. The first column for each systolic and diastolic sub-group (i.e. column 1, 4, 7, and 10) shows the treatment effect without any control variables. The second column (i.e. 2, 5, 8, and 11) includes control variables as stated previously and the third column (i.e. 3, 6, 9, and 12) includes physical activities as an additional control variable. Awareness and treatment columns show lower observations than prevalence columns because by construction the denominator for both awareness and treatment rate is the hypertensive individuals only. Number of observations for the control rate is even lower because its denominator is hypertensive individuals who received treatment only.

Table 9-6 Effect of the JKN programme on prevalence, awareness, treatment, and control of hypertension (Logit estimation)

OLS	Prevalence#			Awareness^			Treatment†			Controlled††		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel 1 JKN Contributory												
DID effect	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	0.12** (0.05)	0.08* (0.04)	0.07* (0.04)	0.10*** (0.03)	0.11*** (0.04)	0.10*** (0.04)	0.10 (0.11)	0.07 (0.10)	0.11 (0.09)
Observations	18,102	18,100	18,030	5,260	5,260	5,218	5,260	5,260	5,218	726	726	717
Panel 2 JKN Subsidised												
DID effect	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	-0.01 (0.02)	-0.03 (0.02)	-0.02 (0.02)	0.13 (0.08)	0.14** (0.07)	0.13* (0.07)
Observations	21,110	21,110	21,022	6,200	6,200	6,148	6,200	6,200	6,148	810	810	800
Control variables	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Health behaviour	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

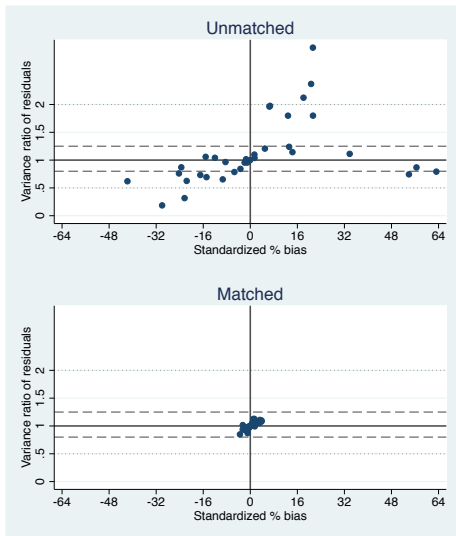
#Prevalence: The union of elevated blood pressure (Systolic/Diastolic > 140/90 mmHg) and self-reported of hypertension diagnosis/total sample

^Awareness: Hypertensive individuals who were aware of their condition/hypertensive individuals

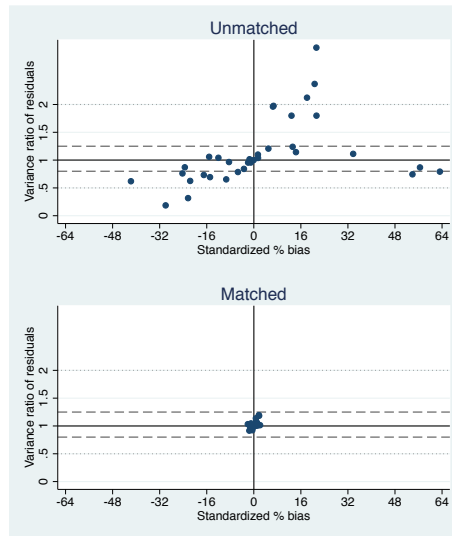
†Treatment: Hypertensive individuals who took medication to lower their blood pressure/hypertensive individuals

††Control: Hypertensive individuals with normal BP and taking medication/hypertensive individuals who took medication

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01; standard errors are in parentheses. Standard error is clustered at the individual level. All models are estimated by logit model. All estimates are calculated as a marginal effect following calculation by Puhani (2012) therefore they can be interpreted as a percentage change. Control group for both panels are the uninsured group. The first column for each systolic and diastolic sub-group (i.e. column 1, 4, 7, and 10) shows the treatment effect without any control variables. The second column (i.e. 2, 5, 8, and 11) includes control variables as stated previously and the third column (i.e. 3, 6, 9, and 12) includes physical activities as an additional control variable.



a. NNM (Contributory)



b. Kernel

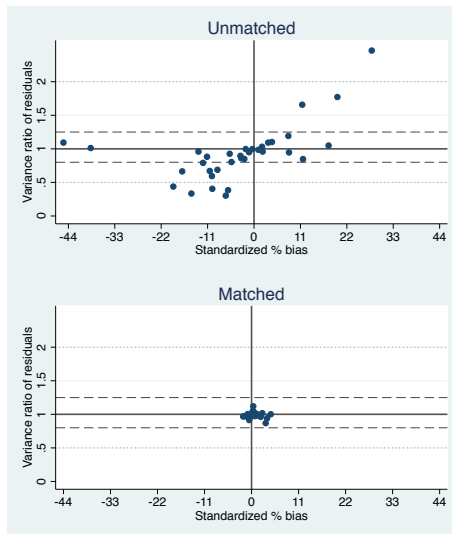
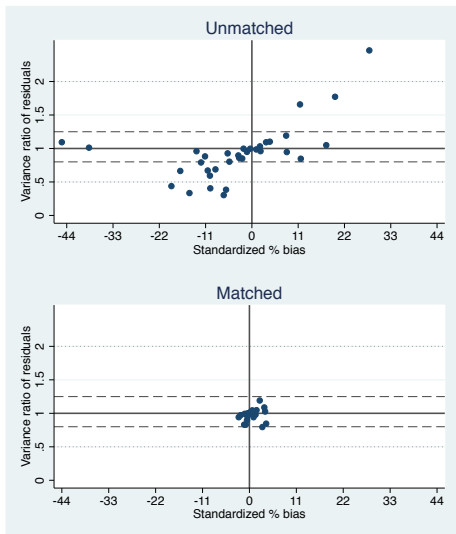


Figure 9-5 Bias reduction from propensity score matching

Note: NNM = nearest neighbour matching

Points represent the control variables used in propensity score estimation.

X-variable: standardised percentage bias → closer to zero, the better.

Y variable: variance ratio of residuals → closer to zero, the better.



Table 9-7 The effect of JKN programme estimated by PSM-DID

	Systolic		Diastolic		Prevalence		Awareness		Treatment		Controlled	
	NNM (1)	Kernel (2)	NNM (3)	Kernel (4)	NNM (5)	Kernel (6)	NNM (7)	Kernel (8)	NNM (9)	Kernel (10)	NNM (11)	Kernel (12)
JKN Contributory												
PSM	0.878 (0.883)	0.255 (0.824)	0.395 (0.486)	0.028 (0.451)	0.010 (0.018)	-0.002 (0.017)	0.110** (0.110)	0.141*** (0.046)	0.071* (0.041)	0.071* (0.039)	0.290* (0.170)	0.159* (0.051)
DID	0.688 -0.603	0.158 -0.561	0.389 -0.397	0.002 -0.370	-0.001 -0.017	-0.007 -0.016	0.135** -0.053	0.100*** -0.045	0.090 -0.048	0.292** -0.163	0.450** -0.180	0.427** -0.175
JKN Subsidised												
PSM	0.289 (0.608)	0.388 (0.562)	0.275 (0.318)	0.170 (0.296)	0.021 (0.013)	0.020 (0.012)	0.040 (0.033)	0.047 (0.030)	-0.041 (0.022)	-0.031 (0.020)	0.041 (0.035)	0.050*** (0.031)
DID	0.023 (0.427)	0.019 (0.396)	0.044 (0.263)	0.001 (0.245)	0.011 (0.012)	0.011 (0.011)	-0.050 (0.031)	-0.041 (0.028)	-0.500 (0.500)	-0.485 (0.181)	0.000 (0.000)	0.052 (0.116)

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ ; standard errors are in parentheses. Calculations based on 902 observations of JKN contributory, 2403 observations of JKN subsidised, and 8137 observations of uninsured group that fulfil common support condition.

Table 9-8 Heterogeneity of the JKN effect, by urban/rural area and socioeconomic status (OLS estimation)

VARIABLES	JKN Contributory						JKN Subsidised					
	Systolic	Diastolic	Prevalence	Awareness	Treatment	Controlled	Systolic	Diastolic	Prevalence	Awareness	Treatment	Controlled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - Urban vs Rural												
Effect on rural	-2.35*	-0.04	-0.05	-0.04	0.03	-0.07	-0.43	-0.06	-0.00	0.10***	-0.01	0.29***
	(1.25)	(0.77)	(0.03)	(0.08)	(0.08)	(0.20)	(0.66)	(0.39)	(0.02)	(0.04)	(0.03)	(0.10)
Additional effect on urban relative to rural	3.21**	-0.13	0.06	0.21**	0.12	0.37	0.68	0.38	0.01	-0.13**	-0.01	-0.37***
	(1.63)	(1.00)	(0.04)	(0.10)	(0.09)	(0.23)	(1.08)	(0.63)	(0.03)	(0.06)	(0.05)	(0.14)
Observations	18,078	18,078	18,078	5,251	5,251	726	21,083	21,083	21,083	6,188	6,188	809
Panel B - Poor vs Rich												
Effect on the Rich	-0.12	-0.68	-0.00	0.12**	0.14***	0.19*	-1.18	-0.89*	-0.02	0.04	-0.03	0.08
	(0.73)	(0.47)	(0.02)	(0.05)	(0.04)	(0.10)	(0.79)	(0.46)	(0.02)	(0.04)	(0.04)	(0.10)
Additional effect on the poor relative to the Rich	-0.31	2.37	-0.04	-0.10	-0.15*	-0.26	1.57	1.76***	0.03	-0.02	0.01	0.12
	(1.94)	(1.23)	(0.05)	(0.11)	(0.08)	(0.24)	(1.16)	(0.67)	(0.03)	(0.06)	(0.05)	(0.14)
Observations	18,087	18,087	18,087	5,253	5,253	726	21,095	21,095	21,095	6,191	6,191	809

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ ; standard errors are in parentheses. Poor is defined as an individual who belongs to wealth quintile 1 and 2 based on asset index. Rich is defined as an individual who belongs to wealth quintile 3-5. All models are estimated by OLS. All estimates can be seen as a percentage change.

#### 9.4.5 Test of the parallel trends assumption

The most important assumption in DID is the parallel trends assumption that both insured and uninsured groups followed the same outcome trajectory prior to the introduction of JKN programme. As previously described, one of the ways to test this assumption is to run a placebo regression in which the treatment variable is applied to past outcomes. If the assumption was not violated, we would expect zero effect of the treatment variable on these outcomes. Table 9-9 presents the result of the placebo regression on systolic and diastolic blood pressure levels in 2000. None of coefficients were statistically significant, which suggests the assumption was not violated, and the estimation results are reliable.

*Table 9-9 Placebo test of the JKN effect on systolic and diastolic*

	JKN Contributory	JKN Subsidised
Systolic (mmHg)	1.34 (1.03)	0.13 (0.67)
Diastolic (mmHg)	0.85 (0.58)	-0.44 (0.37)
Observation	15,463	18,097

*\*p<0.1; \*\*p<0.05; \*\*\*p<0.01; standard errors are in parentheses.*

### Section 9.5 Discussion

In this chapter, I used DID and PSM combined with DID to evaluate the effect of JKN on blood pressure (SBP and DBP) as well as the level of prevalence, awareness, treatment and control of hypertension. Overall, the effect of JKN varied between the contributory and the subsidised groups compared to those who were uninsured. Subgroup analyses by locality of residence and household wealth also revealed further heterogeneity of effects on some, but not all, outcomes. While the JKN programme had no significant effect on systolic and diastolic blood pressure, the data suggest a positive effect on increasing awareness, treatment, and control of hypertension

among the contributory group, although the latter finding was not always consistent. In addition, the JKN programme appeared to have only limited effect on improving control of hypertension among the subsidised group. The overall finding on control rate of hypertension needs to be interpreted carefully because of the inconsistency of the findings across different estimation strategies. It is possible that the insufficient sample size may dampen our effort in estimating the true treatment effect on control rate of hypertension. For example, the sample for control of hypertension was taken from number of people who received anti-hypertensive treatment. Based on Figure 3, only 918 individuals reported taking anti-hypertensive medication from medical providers in 2014.

The increased effects on increasing awareness and treatment among the contributory group were expected based on my finding in Chapter 7. I have shown that the contributory group has increased utilisation on outpatient and inpatient services. As awareness and treatment can be used as proxies for access to diagnosis of hypertension and hypertension medication, my findings in this chapter suggest that the JKN programme improved access to medical care among the contributory group.

In this analysis, I found no overall effect of JKN on reducing systolic and diastolic blood pressure among the insured. This finding is consistent with several evaluation studies in other countries that also reported no insurance effect on health status. One explanation is the short time period between the introduction of the insurance programme and the start of its evaluation (King et al., 2009; Chen and Jin, 2012; Cheng et al., 2015), meaning sufficient time has not passed for the programme's effect on health status to be reflected in the data. Indeed, JKN was introduced in January of 2014, and the data were collected in September 2014. The effect on health status may only be realised if either utilisation or financial protection were affected by the insurance programme. By contrast, health insurance arguably impacts utilisation of health care and OOP health expenditure more directly as depicted in the conceptual framework in Figure 9-1n Figure 9-1. Therefore, the findings in this analysis are consistent with the theorised pathway between health insurance and utilisation.

Very few studies evaluating the impact of introducing health insurance programmes in LMIC examine population health outcomes, with most studies focusing on utilisation or financial protection as outcomes of interest (Acharya et al. 2013, Giedion et al. 2012). To illustrate, in the review I conducted in chapter 4, I found only 12 studies evaluating health status as the outcome, compared to 40 studies on utilisation and 46 studies on financial protection. Of these 12 studies, two evaluated the impact of health insurance on hypertension. One of these studies evaluated the effect of the Seguro Popular insurance programme in Mexico on hypertension treatment and control (Bleich et al. 2007). The authors found that being insured was associated with greater use of antihypertensive treatment and better blood pressure control. However, cross-sectional data from a single survey were used to compare the insured with the uninsured populations. Selection bias was also likely in the voluntarily insured group, which limits the value of a comparison of insured with uninsured groups. That is, patients with better health literacy, more health-seeking behaviour, and more severe hypertension may be more likely to enrol in an insurance programme and may be more likely to start and adhere to an antihypertensive treatment regimen, independent of their insurance status. Findings from my study support this notion because treatment coverage for hypertension in the uninsured population in the programme area was lower compared with treatment coverage in the (equally uninsured) control area, and patients with more severe hypertension were more likely to enrol in the programme.

The strength of my study is the elimination of selection bias by using analysis with longitudinal data from longitudinal surveys. The other study evaluating the effect of health insurance on hypertension came from Nigeria. In contrast to my findings, the authors evaluated the effect of community-based health insurance and found that the insurance programme was associated with a significant decrease in blood pressure among the hypertensive people (systolic: -5.24 [95% CI: -9.46 to -1.02] and diastolic: 2.16 [95% CI: -4.27 to -0.05]) (Hendriks et al., 2014). While the authors used a similar technique to what I used in this thesis, they limited their sample to only hypertensive individuals identified in baseline survey. In my analysis, I pooled all individuals despite their hypertensive status in baseline and estimated the overall effect of JKN programme on both systolic and diastolic. However, restricting the

analysis to only hypertensive individuals (either systolic  $\geq 140$  mmHg or diastolic  $\geq 90$  mmHg) identified in the 2007 (baseline) survey, the findings did not differ substantially (result not shown); the effect of JKN on either systolic or diastolic was still not statistically significant. It is also worth noting that the follow-up survey in Nigeria was conducted two years after the introduction of the insurance programme, which further strengthens the suggestion that sufficient time should be allowed to pass before the impact on health status can be observed.

Evidence from developed countries, point to a protective effect of health against hypertension among its enrollees. One of the most famous health insurance experiments in the U.S., the RAND Health Insurance Study, collected cross-sectional data from 3,958 people between the ages of 14 and 61 and had been randomly assigned to a set of insurance plans for three or five years. One plan provided free care; the others required enrollees to pay a share of their medical bills. The study showed that diastolic blood pressure among the insured was 3 mmHg lower than the uninsured. They further explained that this reduction could be explained by better case finding of hypertension resulting from reduced barriers to accessing primary care and not by altering health habits associated with cardiovascular, such as smoking (Brook et al., 1983). My finding that the JKN programme was associated with increased awareness rate of hypertension among the enrollees in the contributory group is consistent with the findings from the RAND study.

Similar findings were observed from the Oregon Health Insurance Experiment, an experimental study of health insurance expansion for low-income adults through a lottery drawing. Adults randomly selected in the lottery were given the option to apply for health insurance, but not all lottery winners enrolled in the health insurance. In that study, health insurance was associated with 7.16 percentage point reduction in the prevalence of hypertension (p-value: 0.39) (Baicker et al., 2013). The authors argued that the sample size of their study might not strong enough to detect any treatment effects among people with hypertension. Nevertheless, they also found a decrease of more than 20% in the predicted 10-year cardiovascular risk or a

decrease of more than 10% in predicted cardiovascular risk among the participants with high-risk of cardiovascular diagnoses before the lottery.

In this chapter, I evaluated the impact of JKN on health status, specifically looking at hypertension in the study population. The data suggest the JKN effect on health status is limited although there is an indication that JKN programme encourages better blood pressure management through increased awareness, treatment, and control. I also found that the benefit of the JKN programme was stronger among the richest group, as reflected in a stronger effect in the contributory group and limited effect in the subsidised group.

## **Chapter 10 Discussion**

### **Section 10.1 Introduction**

The research carried out for this thesis explores the expansion of the public health insurance programme in Indonesia, focusing on the most recent insurance scheme – the JKN programme – introduced in 2014. Within the thesis, I have critically reviewed the evidence gathered from low- and middle-income countries (LMICs) on the effectiveness of public health insurance in improving access to care, financial protection and health status. I have also emphasised the importance of controlling for selection bias in health insurance evaluation studies and reviewed the methods that were used in the research in LMIC settings. Finally, the main aim of this thesis was to measure the impact of the JKN programme on health care utilisation, financial protection and health status. More specifically, the study's objectives were to measure:

- i. The impact of the JKN programme on utilisation of health care measured by both the probability and frequency of outpatient and inpatient visits;
- ii. The effect of the JKN programme on average individual out-of-pocket (OOP) health expenditure and the incidence of catastrophic health expenditure at household level;
- iii. The effects of the JKN programme on reducing blood pressure and hypertension prevalence rates and increasing hypertension awareness, treatment and control.

In this chapter, I will synthesise and explore the findings taking into account the Indonesian context, the body of evidence available on the effectiveness of public health insurance in LMIC settings, and the health insurance theories explored in previous chapters. Additionally, I will provide a reflection on the strengths and limitations of the methods. Several suggestions based on the evidence gathered in this thesis are offered for researchers and policymakers regarding potential strategies for improving the effectiveness of the health insurance programme in Indonesia.



## **Section 10.2 Discussion of findings**

### **10.2.1 The health insurance system**

No country relies on a single source of funding for health care. Countries typically use one of the four main funding models as the principal way of paying for health care, alongside elements of the others. However, there is lack of evidence to suggest that one funding model or particular mix of funding mechanisms is inherently better in delivering cost-effective health care (OECD/EU, 2016). The precise combination of funding sources in use develops over time, based on a country's context, history and social values. Nevertheless, there are several patterns that can be observed from various successful schemes in LMICs.

First, I found that community-based health insurance (CBHI) is commonly adopted by low-income countries that have limited monetary and human resources in establishing either social health insurance or a tax-based insurance system. CBHI may act as the first step towards introducing the concept of insurance to the general population. If the CBHI scheme is successful, the government may scale it up nationally by retaining the multiple payer structure (for example, Rwanda) or forming a single payer system (for example, Ghana and The Philippines).

Second, social health insurance is usually popular among middle-income countries which have sizeable formal employment sectors (for example, Mexico, Colombia and The Philippines) while tax-based insurance is uncommon in LMICs. In the case of the latter, it is argued that establishing such a system requires a strong political movement focused on providing access to health care for everyone (Svedoff, 2004). For example, Malaysia, an upper middle-income country, has a national public health system primarily funded by general tax payments and this has existed since its independence in 1957 (Yu, Whynes and Sach, 2008). Another example is Ghana which has established a national health insurance system primarily funded (approximately 70 percent) by value-added tax, but it still requires premium contributions from its enrollees (Agyepong et al., 2016).

Third, regardless of the difference in its implementation, LMICs adopting either SHI or CBHI systems have encountered issues in enrolling new members and retaining current members, particularly among informal sector employees. If the insurance scheme fails to recruit more members when the demand for health care increases, the effectiveness of its risk pooling will deteriorate which will further deter people from joining. For example, CBHI schemes in Rwanda and Uganda showed weak financial sustainability because of low renewal rates, high claims-to-revenue ratios and high operational costs (Spaan et al., 2012). While SHI is usually characterised by its mandated contribution, many LMICs have yet to develop a reliable method to enforce it, particularly among informal sector employees.

Fourth, LMICs which claim to have achieved universal health coverage often do not rely on a single public insurance scheme; a separate scheme for civil servants or employees in the formal sector usually exists and offers more comprehensive medical benefits. In Thailand, formal public and private sector employees were covered by the Civil Servant Medical Benefit Scheme (CSMBS) and Social Health Insurance (SHI), both of which existed prior to the introduction of the Universal Coverage Scheme (UCS) for informal sector employees and the poor population. The *Rwandaise d'assurance maladie* (RAMA) is a mandatory scheme for Rwandan government employees and their dependants and covered 2.3 percent of the population in 2007 (Saksena et al., 2010). RAMA is considered to have superior medical benefits compared with the national CBHI scheme offered to the general population. In Mexico, the *Instituto Mexicano del Seguro Social* (the Mexican Institute of Social Security, or IMSS) serves formal workers in the private sector and covers approximately 40 percent of the Mexican population (Lakin, 2010). This separation is often caused by the resistance from stakeholders within the existing scheme. For example, Thailand is still struggling to unify CSMBS into UCS due to heavy resistance from the union of health care providers who favour the fee-for-service payment structure employed by the CSMBS (Tangcharoensathien et al., 2018). In Mexico, the IMSS union of health providers also opposed the integration of the IMSS into a unified public insurance scheme because the proposed unified scheme would have weakened the labour relations within the IMSS (Lakin, 2010).

## 10.2.2 Access to care

### 10.2.2.1 Defining access to care

Measuring access to care is key to understanding and developing health policy, but there is a lack of agreement on the definition of access in the literature. The most commonly cited framework of access to care is Andersen's access to care model which was developed in late 1960s to explain factors affecting access to medical care in the United States of America (Andersen, 1968). Andersen argued that access can be broken down further into two distinct components, potential access and realised access. Potential access is measured by enabling factors that give patients the opportunity to access care. For example, health insurance is assumed to provide greater access to care for patients. Therefore, health insurance coverage indicates potential access that may or may not be realised by the patients (Andersen, 2008). Another example is the availability of health care facilities. Individuals who live in an area with a greater choice of health care providers are considered to have better potential access to care (Gulliford et al., 2002). Potential access may help to explain how patients are able to access the care but it does not explain whether patients actually use the care – this is measured by realised access. Realised access is commonly measured by utilisation indicators, including outpatient, inpatient, dental, maternal and emergency care. Andersen's model is therefore useful as a conceptual framework for exploring the relationship between potential access (for example, health insurance or other financial incentives) and realised access.

Measuring utilisation can be seen as an objective indicator of access and this explains its popularity in studies of access to care (for example, Bernal, Carpio and Klein, 2014; Sparrow, Suryahadi and Widyanti, 2013; Sommers, Baicker and Epstein, 2012; Kisa and MZ, 2007). Findings from the reviews in Chapters 4 and 5 have indicated that access to care is uniformly defined as utilisation of health care which may vary from visits to primary care clinics to hospitalisation. However, solely measuring utilisation may prove inadequate for exploring the reasons why access is not realised. Another alternative model has been proposed by Penchansky and Thomas (1981) as a critique of the initial 1960s Andersen model. They assert that access is a

multidimensional term which makes it impossible to measure using one factor alone. They suggest that access has five interrelated dimensions, including availability (for example, the supply-side of health services), accessibility (for example, transportation), accommodation (for example, quality and support systems in health care facilities), affordability (for example, the price) and acceptability (for example, trust between patient and doctor). This model can be seen as an extension of the potential access concept, as all five dimensions are closely related to the predisposing characteristics and enabling factors found in Andersen's model (Andersen, 1995). However, Pechansky and Thomas' model regards all five dimensions as equal which means improving access to care cannot be reached successfully without considering all five dimensions. Providing health insurance may increase the affordability dimension, but it may not be enough to build trust between patient and provider (acceptability) or cover the transportation costs required to reach the clinic or hospital (accessibility).

#### *10.2.2.2 A stronger positive impact among the contributory group*

From my empirical study discussed in Chapter 7, I found that the JKN programme has a positive effect in increasing utilisation for its enrollees and this effect is stronger among the contributory group. Approximately, In addition, the insured in the contributory group are more likely to initiate the seeking of care in formal health care facilities, such as clinics, private GPs and hospitals, as well as increase the frequency of the visits.

This increased utilisation may be associated with the concept of 'moral hazard', found in the economic literature. Moral hazard dictates that the increased consumption of care is unnecessary and welfare decreasing because the insured take advantage of the price reduction offered by the insurance and utilise the care more than they should (Zweifel and Manning, 2000; Pauly, 1974). The potential for moral hazard may be strong in the context of the JKN programme because it offers very generous medical benefits with almost no cost-sharing. However, this moral hazard arguably should not be always seen as welfare-decreasing. According to Nyman (2003), the

insured would only gain benefits from the insurance when they are ill. The insurance offers an income transfer from the healthy to the sick, which allows the sick to access medical care that would be otherwise unaffordable. This is especially true for inpatient care because it often involves more complicated medical treatments and it is more expensive than outpatient care. In addition, it is quite implausible to assume that being hospitalised is desirable for many healthy individuals. Under this condition, this 'moral hazard' can be considered an efficient behaviour because the resulting use of care is justified by the medical need for care.

An important condition in regarding increased utilisation as an inefficient moral hazard is the trade-off between personal health practice and use of curative medical treatment (de Preux, 2011). The insured may engage in more risky health behaviour and use less preventive care, which may lead to increased use of curative care that could have been avoided if the patients were still uninsured (Qin and Lu, 2014). This is often known as 'ex-ante moral hazard' (Zweifel and Manning, 2000). However, it does not always mean that the insured are more likely to start engaging in risky behaviour, for example, conversion from a non-smoker or a non-alcoholic to a smoker or an alcoholic. Dong (2013) investigated the differences in moral hazard in the extensive and intensive margins of risky behaviour. He found that while health insurance was not significantly associated with the probability of participating in unhealthy behaviours, among those who participate in unhealthy behaviours, health insurance may increase the quantity of unhealthy behaviour. Thus, the insurance may incentivise a smoker to smoke more cigarettes but does not influence a non-smoker to try a cigarette for the first time.

The evidence for ex-ante moral hazard in the context of the JKN programme has not been documented elsewhere as yet. The evidence from my study (see Table 9-2) shows a general trend of an increase in the number of people initiating cigarette smoking but equally an increase in the number of people stopping smoking. For example, in the contributory group, the percentage of people participating in medium-level smoking (11-20 cigarettes/day) increased between 2007 and 2014, and both the uninsured and subsidised groups demonstrated an increased

percentage of heavy smoking (>20 cigarettes/day) between the two waves. Another example can be taken from looking at physical status which measures the type and frequency of physical activity at work, at home and during exercise. All three groups show a similar, increased trend of living a more sedentary life. While Indonesian people are engaging in less healthy behaviours, it is unlikely that JKN insurance can explain this phenomenon because the uninsured group and both JKN insured groups exhibit a similar trend of increased levels of smoking and lower levels of physical activity. Therefore, there is not enough evidence to claim that the JKN programme affects the health behaviour of its enrollees.

In addition to moral hazard, a more serious possible explanation for increased medical care usage among the contributory group is 'adverse selection'. My analysis found that the contributory group (those who self-selected to participate in the JKN programme) increased their consumption of medical care at a higher rate than the subsidised group. If their decision to enrol in the JKN programme can be explained by their health status, the case for adverse selection is likely to be true. From the logit regression of participation in the JKN programme on baseline characteristics in 2007, the number of acute conditions and the presence of disability were significantly associated with the decision to participate in the JKN contributory group (see Table A-5 in the appendices). Meanwhile, none of the health status variables were significant in the JKN subsidised participation logit model (see Table A-6 in the appendices). This evidence suggests the presence of adverse selection among the JKN contributory group but not the subsidised group.

#### *10.2.2.3 A limited effect among the subsidised group*

In the review in Chapter 4, it was predicted that health insurance would be most beneficial in increasing access to formal health care facilities and that poor people may gain greater benefits from health insurance (Acharya et al., 2013; Giedion et al., 2013). In my empirical analysis in Chapter 7, I found that the subsidised group was more likely to utilise both outpatient and inpatient care but only marginally compared with the increased utilisation rate of the contributory group. My finding,

therefore, does not support the suggestion made in Chapter 4 that low-income individuals may reap more benefits from public health insurance.

When the estimation model was stratified by density of health facilities in a given area, the effect was larger and more statistically significant for the subsidised group living in an area with high availability of health facilities. This finding agrees with the conceptual framework of access to care: that the need for health care can only be realised with the fulfilment of adequate enabling factors, including health insurance and proximity to the nearest health facilities. In itself, health insurance acts as a demand-side incentive that may help patients to pay for the cost of medical treatment, boosting the affordability of seeking care. However, improving access to care requires the fulfilment of the other four dimensions of access, which is accessibility, accommodation, availability and acceptability (Penchansky and Thomas, 1981). The JKN programme is unlikely to increase the availability of health facilities for several reasons. First, Indonesia has a decentralised health system, as described in Chapter 3, which provides greater autonomy to local areas in running general health care activities, including building new facilities and their maintenance. Thus, increasing the availability of public health facilities is unlikely to happen in the short term because it requires extensive discussion between the central and local governments in order to reach an agreement. Second, the JKN programme adopts a capitation payment system for primary care and a diagnosis-related group (DRG) system for hospital care, both of which are unpopular among private providers. Private practices in rural and remote areas are often staffed by doctors who work in public health centres in the daytime and open their own practices, often in their own homes, at night time. They tend to favour a fee-for-service system to boost their income and it is unlikely that they would also accept JKN patients.

Other poverty alleviation programmes, for example unconditional or conditional cash transfer, could also potentially increase health care utilisation because the recipients of such programmes may receive extra income to spend on health care, but this is likely to be a relatively small impact. Examples of other poverty alleviation programmes are Unconditional Cash Transfer (UCT) and Conditional Cash Transfer

(CCT). It is likely that individuals in the JKN subsidised group are also recipients of UCT and CCT because the selection criteria for both programmes may overlap. In fact, 51 percent of individuals in the subsidised group also reported receiving UCT in 2014, compared with one percent in the uninsured group. Meanwhile, the number of CCT recipients is far lower in both the subsidised and uninsured groups, nine percent and one percent respectively, because CCT is only available in several urban areas. In my analysis, both UCT and CCT status have been controlled for by adding those variables into the PSM-DID estimation model. However, I cannot fully account for all of the other poverty alleviation programmes that may influence both the decision to seek care and insurance selection. To establish the likelihood of other confounding factors that were not controlled for by the PSM-DID strategy, and which may change the findings, a sensitivity analysis based on the Rosenbaum bounds approach was also conducted (see Tables A-3 and A-4 in the appendices). The effect of an unobserved bias would need to be 1.3 times the effect of having JKN insurance on inpatient care to undermine this study's findings. As the UCT and CCT programmes have been controlled for in my analysis, other smaller poverty alleviation programmes that are not specifically targeted to health are unlikely to influence the decision to seek formal health care.

A local government in the province or district area may also provide an additional health insurance programme (collectively called *Jamkesda*) which aims to close the coverage gap, but this policy is not implemented across all local authorities. In this study, individuals who reported having *Jamkesda* are excluded because I am interested in the effect of the national health insurance programme, not the local setting. Furthermore, *Jamkesda* has too much variation in terms of coverage and benefit structures, making it difficult to identify a causal relationship between the insurance and the outcome. Nevertheless, an evaluation study of *Jamkesda* discovered that it only marginally increased outpatient utilisation, while providing little to no financial protection (Sparrow et al., 2017) This finding is consistent with my result that the subsidised health insurance programme has a rather limited effect on utilisation.



It is worth noting that the contributory group is not the major contributor to the JKN programme, representing only 16.4 percent of total JKN membership. The majority of JKN members are in the subsidised group (60 percent) followed by salaried private workers and civil servants (23.6 percent). Given the fact that the subsidised group accounts for the largest proportion of the JKN insured population, the subsidies paid for by the government are likely to contribute more to the overall JKN budget. This implies a potential inequity in how government subsidies are being targeted in the sense that the poor do not receive the benefit from the subsidy. This inequity issue is exacerbated by the fact that the JKN effect is much stronger in areas with a higher density of health care facilities. Since subsidised group members are more likely to live in rural areas with limited health care facilities, we can expect to see that the insurance has a limited effect in removing barriers to accessing care. Insurance may ease the financial barriers associated with the fees for medical treatment (i.e. affordability) but may not be adequate for removing other barriers to access, such as the cost of transportation (accessibility) or the availability of primary clinics and hospitals. Improving access to care among individuals in rural and remote areas remains a significant challenge for the Indonesian government: a problem that cannot be solved solely by the introduction of public health insurance for all.

### **10.2.3 Financial protection**

#### *10.2.3.1 The limited effect of the JKN programme on OOP health expenditure*

Financial protection is commonly measured by identifying the medical costs that patients have to spend 'out-of-pocket', often called out-of-pocket (OOP) health expenditure. Health insurance is expected to reduce this expenditure. However, the overall evidence on the effect of health insurance in reducing OOP expenditure is less homogeneous compared with its effect on utilisation. Findings from Chapter 4 show that the majority of studies identified that health insurance had a beneficial effect in reducing OOP expenditure, however in specific contexts, health insurance may increase OOP expenditure instead (Wagstaff et al., 2009; Wagstaff and Lindelow, 2008; Ekman, 2007; Dong et al., 1999;). The updated review in Chapter 5 identified additional studies on financial protection and found a similar pattern of mixed

findings: 16 out of 46 studies found no effect and four studies showed increased OOP health expenditure following the introduction of health insurance. Restricting the evidence to randomised trials in LMICs, three studies reported reduced OOP health expenditure (Levine, Polimeni and Ramage, 2016; Grogger et al., 2015; Fink et al., 2013) and one study reported no effect (Raza et al., 2016).

Studies from developing countries also provide evidence that subsidised public health insurance does not always reduce health spending. Bernal et al. (2014) found that subsidised health insurance in Peru increased OOP health expenditure, particularly at the high end of the distribution of expenditure. They argue that their finding may be explained by the idea that individuals reach maximum levels of coverage and then pay for complex treatments themselves. Wagstaff et al. (2009) evaluated a heavily subsidised voluntary health insurance programme for rural residents in China and found that it did not reduce OOP health spending per outpatient or inpatient visit. They suggest that their finding might be driven by a fee-for-service payment mechanism which may result in higher health care costs. Palmer et al. (2015) evaluated Vietnam's health insurance for children and also found that the insurance did not decrease OOP health expenditure. They linked this finding to the fact that the enrollees sought care in a more specialised facilities without seeking a referral from a primary facility, which resulted in the enrollees making their own health care payments.

Within Chapter 5, I also identified two studies from Indonesia offering conflicting evidence in relation to the evaluation of Askeskin, a subsidised health insurance programme for poor people in Indonesia. One study found that Askeskin reduced OOP health expenditure while the other found opposite findings (Aji et al., 2013; Sparrow, Suryahadi and Widyanti, 2013). Sparrow, Suryahadi, and Widyanti (2013) evaluated the Askeskin programme by analysing national socioeconomic survey (Susenas) panel datasets (2005–2006) using a PSM-DID approach and found that Askeskin increased OOP health expenditure and budget shares, particularly in urban areas. However, they were unable to discern the reasons for this increased spending. Meanwhile, Aji et al. (2013) evaluated Askeskin by analysing the IFLS 2000 and 2007

datasets with Instrumental Variables (IV) and Fixed Effect (FE) and found that Askeskin reduced OOP health expenditure, even though it was only significant at the 10 percent level. I applied a different specification for my model compared with Aji et al.'s model by including more objective need factors, such as the number of acute and chronic conditions and disability conditions, whereas Aji et al. only included a dummy for subjective well-being and a dummy for limitations in relation to activities in daily life.

Upon reflection of the evidence provided in Chapters 4 and 5, the hypothetical direction of the effect of health insurance on financial protection was becoming less clear. Nevertheless, my empirical findings from Chapter 8 found that the JKN programme had no significant effect on both individual and household OOP health expenditure, either for outpatient or inpatient care. While the coefficients of OOP health expenditure were positive in almost all of the models, none of these were statistically significant at the 5 percent level. Only the overall household OOP health expenditure had a positive coefficient that was significant at 10 percent (under the PSM-DID model). In addition, I also found that the JKN programme, overall, had no significant effect on catastrophic health expenditure events.

It is also likely that people did not seek care before the introduction of the JKN programme period and still did not seek care after the treatment period, hence their zero spending. This implies that the utilisation effect precedes the expenditure effect, as discussed in Chapter 4. When the insurance fails to increase utilisation, it is expected that there will be no effect on the health expenditure. In this study, this scenario is unlikely because the JKN programme increased utilisation for both the contributory and the subsidised groups.

Another explanation is that some of the JKN enrollees might prefer not to use JKN benefits for seeking care, especially in outpatient care. Qualitative findings from two randomised trials in health insurance suggest that patients perceived the quality of services from providers contracted by the health insurance scheme to be lower than those offered by private providers, and that this lower quality may be associated with

the capitation payments employed by the insurance schemes (Raza et al., 2016; Fink et al., 2013). Incidentally, the JKN programme also uses capitation to pay primary care providers in both public health centres and contracted private provision. Capitation entails that health care providers receive an initial lump sum of money for patients who register with them and in return agree to provide services in the future under conditions and terms laid down by the contract with the insurer. Under a simple capitation payment system, providers are encouraged to keep the patients healthy by prioritising preventive care and retain more money by cutting down the amount of medical treatment that is offered (Gosden et al., 2000). This process may lead to a better quality of care, but this will take a long time to happen as clinical processes change slowly. In addition, they may also be disincentivised to perform well for sicker patients as this will attract greater numbers of sick and expensive patients with a flat payment in return (Matsaganis and Glennerster, 1994).

Evidence of the capitation payment effect on the quality of care is mixed. A review undertaken in the United States showed an equal number of the statistically significant positive and negative effects of managed care on quality of care (Miller and Luft, 1997). A qualitative study using in-depth interviews in Burkina Faso found that insufficient levels of capitation payments, the infrequent schedule of capitation payments, and the lack of a payment mechanism for reimbursing service fees were perceived as significant sources of health worker dissatisfaction and loss of work-related motivation (Robyn et al., 2014). Based on my experience working as a doctor in Indonesia, general practitioners are often reluctant to change clinical practice, especially if they perceive the change as a challenge to their authority or a threat to their income. This resistance is similar to doctors' resistance to health care information technology because doctors, just like other professions, tend to maintain the status quo by resisting change and reverting back to the original state (Bhattacharjee and Hikmet, 2007). In response to an initial increase in patient visits due to the introduction of a capitation model (Gosden et al., 2000), doctors are likely to rush the consultation and limit the amount of prescriptions and laboratory testing, which may in turn be perceived by patients as a lower quality of health care. Although it can be argued that patients may be not the best judge of care quality

(Miller and Luft, 1997), reduced prescribing and consultation time are likely to deter patients from seeking care and facilitate the search for private providers.

This limited finding should not be interpreted that JKN has no impact at all since my identification strategy excluded some other population that are covered by JKN. For example, I excluded the JKN enrollees from private formal sector employment and civil servants because of their affiliation with the old insurance system before the introduction of JKN in 2014. It will be a challenge to estimate the causal effect from these populations because any observed effect may be explained by their previous insurance status. However, if one is interested in evaluating the intention-to-treat impact of the new reform, it may be appropriate to include these populations in the treatment group.

It should also be noted that actual cost, rather than potential cost, is analysed in this study. As discussed in Chapter 6, zero health expenditure may reflect the zero cost from utilising health care (i.e. actual cost) or zero from an inability to utilise the care (i.e. potential cost). In this analysis, zero expenditure is therefore considered to be true zero, regardless of an individual's ability to seek care.

Considering the generous medical benefit and almost no cost-sharing mechanism, it is expected that we will see reduced OOP health expenditure among the insured. Nevertheless, no reduction in OOP health spending may still be considered an improvement in the sense that JKN did not increase OOP spending despite increased utilisation. Assuming the insured could not access the care and had zero expenditure prior to the introduction of the JKN programme, having increased utilisation with no increased OOP health expenditure after enrolment implies that the insurance still has a protective effect.

### *10.2.3.2 Possible explanations for non-zero expenditure among the insured*

There are several reasons which may explain the existence of OOP spending among JKN insured patients. First, the providers may prescribe non-generic medication to JKN insured patients. In order to contain the costs, JKN only covers a list of approved medications that often excludes branded drugs. Under JKN regulations, health providers are allowed to prescribe branded drugs and charge the patients for them if there is no alternative (Thabrany, 2016). It is, therefore, in the providers' interest to stock fewer generic drugs as a reason for prescribing branded drugs to JKN patients.

Another likely possibility is the penalty imposed on the insured if they want to upgrade their class of hospital ward (Kesehatan, 2017). A higher class of hospital ward means that patients can enjoy more privacy and access to hospital amenities. The insured from wealthier backgrounds may consider upgrading even with some cost-sharing because they still benefit from the price reduction effect of the insurance, even if it is not totally free. The provider, such as hospitals or clinics, may also prescribe non-generic medications that are not covered by the insurance and pass on this cost to the patients, even though the law stipulates that all of the insured under the JKN programme must not be charged with any fee, with the exception of the hospital ward upgrade (Gultom, Jaya and Atmiroseva, 2015).

Another source of potential spending for JKN enrollees occurs when a patient seeks medical care at a more costly facility. In Chapter 3, it was explained that the JKN contributory group must pay a monthly premium based on the hospital ward class which determines access to certain hospital services. Changing ward class is possible but the patients must pay for the difference in medical costs between the original class and the upgraded class (Kesehatan, 2017). It is also likely that enrollees seek care from secondary or tertiary care facilities without a referral from their GP, which fits with the findings from another health insurance study in Vietnam (Palmer et al., 2015).

A final explanation for additional fees borne by the JKN insured is the persistence of illegal fees that existed prior to the reform taking place. Following the decentralisation policy in the early 2000s, public health facilities have been treated as vehicles for generating rents for bureaucrats in local government (Andrew, 2012). My private discussions with administrative staff when I was working in a public health facility revealed that fees generated by the public health facilities did not go towards their daily budgets but instead served as a source of income for the local government. Furthermore, there was pressure to meet a specific target each month, which resulted in additional pressure to charge patients more fees. As this practice of illegal fees was widespread before the concept of health insurance was introduced, patients might not realise that they are currently being treated unfairly and accept the fees instead.

#### **10.2.4 Health status (blood pressure)**

Improving the population's health status should be the primary long-term outcome of health insurance, but few studies have attempted to measure this, and, unlike utilisation and financial protection, there are multiple choices of outcomes for different medical conditions. An obvious candidate for a more general health outcome measure is the mortality rate because it is often the end result of many acute conditions, such as infectious diseases, obstetrics emergencies, cardiovascular emergencies and cancers. However, unlike in developed countries where the recording of vital registrations has reached >90 percent, vital registration systems in developing countries are mostly incomplete or outdated; this is a particular problem within countries in Africa, Southeast Asia and the Western Pacific (Mathers et al., 2005). Indonesia has no reliable vital registration system in place. The census might provide a reliable estimate of the mortality rate, but the last census was conducted in 2010, four years before the introduction of the JKN programme. The next census will be conducted in 2020. Thus, the mortality rate is not a viable option for my study at the moment.

In Chapter 5, I identified twelve studies, with considerable variation in the precise health measure under consideration, including the mortality rate (child, adult and maternal), the health index, nutrition status for children, and blood pressure. Nine out of twelve of the studies indicated the positive effect of health insurance on various health statuses. For my empirical study on health status in Chapter 9, I chose blood pressure as a health outcome because it has been investigated in other health insurance evaluations, including the famous RAND health insurance experiment and the recent Oregon Medicaid experiment ( Hendriks et al., 2014; Baicker et al., 2013; Sosa-Rubí, Galárraga and López-Ridaura, 2009; Newhouse and Insurance Experiment Group, 1993). My findings showed that the JKN programme had no significant effect on modifying blood pressure in terms of systolic and diastolic measures. However, the JKN programme might increase awareness, treatment and the control rate of hypertension among the contributory group. Meanwhile, the JKN programme had only a limited effect on improving the control rate of hypertension among the subsidised group.

The favourable effect in terms of increasing awareness and rate of treatment among the contributory group is expected based on the findings in Chapter 7. I have shown that the contributory group increased their utilisation of outpatient and inpatient services. As greater awareness and higher treatment rates reflect better access to diagnosis and management of hypertension, an increased effect for both indicators is expected due to better access to care as a result of the JKN programme among the contributory group.

Based on the review of reviews and the updated review in Chapters 4 and 5, there are three main reasons for a 'no effect' finding in the health insurance evaluation. First, the outcome measure may not have matched the goals of the scheme. In the context of the JKN programme, this should not be a major problem because hypertension management can be influenced by health insurance. People with chronic diseases are more likely to gain benefits from health insurance as they are expected to have more visits to the doctors.



Second, health status is considered to be a long-term impact, therefore more time is required for the effects to be revealed in the data. Several evaluation studies in other countries have also reported a no insurance effect on health status but they associated this with the short time period between the introduction of the insurance programme and the start of its evaluation (King et al., 2009; Chen and Jin, 2012; Cheng et al., 2015). Although it has been 5 years since the introduction of JKN (in January 2014), the IFLS data was available only 9 months after the start date (September 2014). Thus, the effect on health status may not yet be fully realised in my data.

The third factor, and perhaps the most important, is the dependence of health status on other short-term effects, as shown in the conceptual framework in Chapter 9. Before the improvement of health status becomes discernible in the data, it requires a prior positive correlation between health insurance and short-term outcomes, such as utilisation of health care services. The effect on health status may only be realised if either utilisation or financial protection are affected by the insurance programme. While there is evidence that JKN has encouraged its enrollees to utilise more health care, financial protection has not yet been ensured. Increased utilisation does not always improve health outcomes (Ross and Mirowsky, 2000). It is therefore suggested that the effects of both utilisation and financial protection have to be realised simultaneously before any effect on health status can be observed.

### **10.2.5 Quality of care**

While the debates in both health financing and quality of care aim to maximise the health benefits with the given resources in a sustainable manner, the financing debate traditionally places less focus on clinical care or patient outcome objectives and more on affordability and efficiency (McLoughlin and Leatherman, 2003). However, the health insurance incentive structure can influence health provider choice between quality and cost (Morrisey et al., 1984). It is argued that in a health care market characterised by high levels of asymmetrical information between

patients, payers and providers, changes in quality are harder to detect when it is costly to monitor and health insurance may incentivise the provider to focus on a measure of quality that is less costly to monitor (Weisbrod, 1991).

The relationship between health insurance and quality of care is less well documented in the literature compared with access to care and financial protection. From the review of reviews in Chapter 3, only one review reports care quality as a component of the study's outcomes. Spaan et al. (2012) found that 3 out of 8 studies reported a positive relationship between community-based health insurance (CBHI) and quality of care but none of these studies is considered to be of a high quality in terms of mitigating insurance selection bias. In theory, CBHI may improve the quality of care through increased utilisation patterns and subsequent income generation. This increased quality may also help to attract more people to join the scheme, but there is little evidence to support the positive impact of CBHI on quality of care. For example, one CBHI scheme in Hanang district, Tanzania, helped to generate additional resources to purchase drugs and equipment and refurbish health facilities (Chee, Smith and Kapinga, 2002) but this improvement was found to be sub-optimal (Kamuzora and Gilson, 2007). Another study focusing on a CBHI scheme in Burundi reported that health workers discriminated against CBHI enrollees and provided preferential treatment to patients paying in cash (Arhin, 1994). It is unlikely that we will see any significant effect on the quality of care, given the sub-optimal income generation due to low enrolment rates encountered in many CBHI schemes in other countries (Hounton, Byass and Kouyate, 2012; Dong et al., 2009; Nkoa and Ongolo-Zogo, 2009; Basaza, Criel and Van der Stuyft, 2008; Kamuzora and Gilson, 2007; De Allegri et al., 2006). The only exception is Rwanda, which achieved the highest rate of health insurance enrolment (81.6 percent by the beginning of 2015) in sub-Saharan Africa (Chemouni, 2018). It is also argued that 'CBHI' in Rwanda has transformed itself into a form of SHI given its mandatory enrolment since 2006 and the more prominent role of central government in the management of all CBHI schemes since 2015 (Ridde et al., 2018), both of which are not traditionally found in CBHI.

Regarding the evidence for quality improvement in countries implementing SHI, Spaan et al. (2013) found that 2 out of 8 studies reported a positive effect on quality of care, measured by the increased rate of antenatal care among insured pregnant women in the Philippines (Kozhimannil et al., 2009) and Ghana (Mensah, Oppong and Schmidt, 2010). However, it can also be argued that increased antenatal care visits are more likely to reflect increased utilisation rather than increased quality of care. Therefore, there is no strong evidence that SHI has any significant effect on quality of care.

Focusing on several randomised controlled studies identified in Chapter 5, quality of care is still not the primary objective of health insurance evaluation. Only one study in the Philippines reported a positive impact on quality of care, but the design of the insurance explicitly included accreditation and a provider payment system which aimed to increase quality of care (Quimbo et al., 2010). While other studies did not include quality measures as their primary outcome, some authors often complemented their findings with qualitative studies suggesting a perceived lower quality of care by enrollees (Levine et al., 2016; Raza et al., 2015; Fink, et al., 2013). In addition, these authors further suggest that the adopted prospective-payment system might impair the quality of care provided by the contracted clinics due to the pressures of needing to preserve more income. Thus, the connection between health insurance and quality of care may depend more explicitly on the chosen payment provider system.

### **Section 10.3      Strengths and limitations**

Alongside the empirical contribution of my evaluation of the JKN programme, I have attempted to offer several contributions to the theories in related fields of study. In terms of the model of access to care, this study confirms that financial incentive in itself is inadequate for improving a population's access to care, especially for poor people. Demand-side initiatives, such as health insurance, vouchers or cash transfers, need to be coupled with improvements in the supply of health care. People who enrolled in the JKN contributory group are more likely to be more affluent than the subsidised group and they already have the advantage of easier physical access to

clinics and hospitals, for example by living in an urban area. The introduction of the JKN programme which aims to cover all citizens by 2019 is the ideal means for them to afford health insurance because its premium is relatively cheaper than private insurance. Borrowing the concept of the 'three phases of delay' from the maternal mortality literature (Thaddeus and Maine, 1994) health insurance is beneficial for removing the first delay of deciding to seek care. The second delay, reaching an adequate health care facility, is related to physical accessibility factors, such as the distribution of facilities, travel time and transportation; and the final delay is related to quality of care at the facility. Individuals who were enrolled in the contributory group had essentially moved past all three barriers, but the subsidised group were still unable to pass the second delay.

The second contribution made by this research is that I am able to show that the impact of the JKN programme is considerably heterogeneous, depending on the enrolees' ability to pay. Had I conducted the study focusing on JKN enrolees as a whole, this difference in impact might not have been revealed. Without any complex analysis, anecdotal evidence from social media and newspapers had already indicated that public health centres and hospitals were overcrowded in the first year of the JKN era (i.e. 2014).

The third contribution relates to the effect of health insurance on financial protection. The JKN programme is perceived as 'free care' for its enrolees and it is assumed that the programme will provide adequate financial protection. However, this study has shown that the JKN programme has not necessarily reduced OOP spending among its enrolees. My finding adds to a growing literature pointing to the inability of health insurance to protect individuals or households from budgetary shocks associated with seeking medical care (Raza et al., 2016; Palmer et al., 2015; Bernal, Carpio and Klein, 2014; Thornton et al., 2010; Wagstaff et al., 2009; Wagstaff and Lindelow, 2008). It was suggested in the previous sub-section that the sources of OOP spending among JKN enrolees include prescription costs, cost-sharing due to an upgraded service and illegal treatment costs.

Lastly, my study is the first health insurance evaluation in Indonesia to attempt to explore the effect on health outcome. The JKN programme had no significant effect on modifying blood pressure in terms of systolic and diastolic measures. However, the programme has had a positive effect on increasing awareness, accessing treatment and controlling the rates of hypertension among the contributory group, although the latter finding did not always show consistent results. Meanwhile, the JKN programme had only a limited effect on improving the control rate of hypertension among the subsidised group. Even if it is argued that health status may not have changed within the several months following the introduction of the JKN programme in January 2014, my study nonetheless reveals an early indication that the enrolees, especially those in the contributory group, may have better access to treatment, which involves hypertension management. Further research on this finding would be welcomed when the next IFLS data is published in two to three years.

Several limitations are apparent, despite my efforts to minimise potential weaknesses in the study. First, some supply factors have not been controlled adequately, such as the distance to the nearest facilities or the quality of the health workforce. These are all factors that may play a role in determining enrolment among the contributory group (Mebratie et al., 2015). IFLS data provide detailed information about health facilities, but this is only available for the facilities that were visited by the respondents. This excludes facilities that might be closer in distance but were not visited by the respondents. If it is argued that better facilities attract more people to use more services, then information about all available health facilities around the sample area is needed. Nevertheless, I have attempted to control for supply-side factors by including the density of health facilities available in the villages / townships in which the respondents were living.

Second, the IFLS is not representative of all Indonesian provinces, and thus it cannot produce a national estimate. The IFLS excluded most eastern Indonesian provinces which are considered to be underdeveloped compared with their western counterparts. Another dataset that encompasses all Indonesian provinces is available from the Indonesian National Socioeconomic Survey (Susenas) (BPS Indonesia,

2017b) but this does not provide adequate health insurance status information or data on health care utilisation. In addition, I found that Susenas is not consistent in collecting health expenditure data, based on my initial effort to analyse Susenas data in my second year. The expenditure variable in Susenas does not measure a household's out-of-pocket expenditure, because it includes the approximated value of any subsidy received by the household in obtaining goods and services. Analysis based on Susenas data has been shown to produce the misleading conclusion of a reduced household health care burden (Johar et al., 2017). In addition to the limitations of the Susenas dataset, the IFLS is the only Indonesian panel dataset available for evaluating the JKN programme, hence its inclusion in this study. Considering IFLS provinces are more developed than the non-IFLS provinces, my findings may show the upper limit of the true impact. It is likely that the JKN programme will have a much more limited impact in the non-IFLS provinces due to the lack of health care facilities in under-developed regions, but the extent to which this is accurate is another empirical question.

Third, this study can only offer a rapid evaluation of the JKN programme considering the short gap between the introduction of the JKN and the IFLS survey. It is possible that the JKN effect will be more discernible once the coverage is nearly universal. Nevertheless, this study still offers an important finding that can inform policymakers in responding to issues related to the implementation of the JKN programme.

Fourth, data collection for the IFLS survey was conducted in the period between September 2014 and March 2015. Since the questionnaire regarding inpatient care has a 12-month recall period, it is likely that patients sought care before the introduction of the JKN programme. Fortunately, IFLS data allow the analyst to separate respondents based on the time of data collection and I have shown that the impact of the JKN programme on inpatient utilisation may change slightly in magnitude but still retain the same direction.

## **Section 10.4      Policy implications**

While it is encouraging to witness the positive impact on utilisation, the greater effect observed on the contributory group indicates a potential adverse selection effect among the more affluent population. Given the fact that the subsidised group accounts for the largest proportion of the insured population, their subsidies paid for by the government also contribute a majority to the JKN budget. As government subsidy is subject to political intervention, the JKN programme should decrease its reliance on the subsidies in order to maintain its sustainability in the long term. Thus, the government should devise a stronger policy in enforcing the mandatory contribution stipulated by the SJSN law. Expanding the membership will increase the risk pooling and decrease the dependency of the JKN budget on government subsidies. This is arguably better to ensure the sustainability of the JKN programme in the future.

Following the limited effect of the JKN programme on the subsidised group despite its large contribution (i.e. the government subsidy) to the JKN budget, it is tempting to compartment the funding between the subsidised and contributory groups to protect the benefit for poorer people. This is unlikely to strengthen the JKN programme because the strength of the JKN programme as a social health insurance, as described in Chapter 2, lies in its massive risk pooling to transfer income from the healthy to the sick. Any division in risk pooling is likely to further weaken the viability of the JKN programme as a single payer system. When the risk pooling is unable to sustain the increased demand from the contributory group, the restriction of JKN medical benefits and rising premiums are inevitable. Catastrophic consequences due to adverse selection are likely to happen, as predicted in Chapter 2 (Cutler and Zeckhauser, 1998). The healthier enrollees will stop their membership, leaving JKN with sicker enrollees who will keep contributing to rising costs. This cycle will continue until JKN is unable to sustain the potential rising costs which may lead to the collapse of the JKN programme and a reversal to its precursors (Askes, Jamsostek, and Jamkesmas) leaving the non-poor people working in informal sectors uninsured.

This study also suggests that the government should put greater focus on the availability of health care facilities in the less affluent areas, such as the eastern part of Indonesia. Health insurance can only be useful if the enrollees have easy access to the nearest health facility. Health insurance may be effective in alleviating the demand-side barrier, but other policies concerning the provision and quality of care remain important in tackling supply-side barriers. This study has confirmed that the effect of the JKN programme on utilisation is stronger in the areas with a high density of health care providers, especially urban areas. Therefore, improving access to care requires a more concerted effort from the local government responsible for the management of the health workforce and infrastructure in their area. The central government may need to devise an incentive for the local governments to encourage their efforts in improving public health infrastructure.

While this study found no statistically significant effect on OOP health expenditure, there is still an indication that the overall health care cost to be paid by the JKN programme will keep increasing considering the positive effect on utilisation. It is inevitable that BPJS as the administrator of the JKN programme needs to mitigate the rising health care costs in the future. Cost-sharing mechanisms might be too politically unpopular and could further deter utilisation among the poorest. Therefore, it is necessary for the JKN programme to move from passive to more strategic purchasing by identifying the services that need to be prioritised and the more cost-effective interventions to be covered by the programme. As the biggest payer in the Indonesian health care system, BPJS can play a more significant role in leading the negotiations of drug prices in Indonesia, which may lower the overall health expenditure in the long run.

The government also needs to invest more in producing good quality data to evaluate the effectiveness of important public policies. Even though IFLS data provide one of the longest sets of longitudinal cohort data, survey funding is primarily received from donor countries. Considering the volatility in development aid and the improved



status of Indonesia from a low-income to a lower-middle income country, it is necessary for Indonesia to become self-sufficient in generating good quality data.

Many LMICs have experimented with the introduction of performance-based financing (PBF) in addition to the existing health insurance scheme, aiming to mitigate the perceived lower quality of care. PBF refers to financial incentives in which payment depends explicitly on the quantity and quality of services delivered (Soucat et al., 2017). In theory, improved quality of care due to the implementation of PBF may make health insurance more attractive, which in turn will increase the enrolment rate. Furthermore, PBF is able to change processes of decision making in allocation away from historical budgeting to a more data-driven output orientation (World Bank, 2014). The move to more strategic purchasing may help the JKN programme to contain the costs while maintaining high quality care, at minimum quality attributes that can be measured efficiently. The government needs to invest sufficient time in designing the PBF scheme, taking into account lessons from other countries and the differences in context and objectives (Renmans et al., 2016).

## **Section 10.5      Agenda for future research**

First, for a better understanding of the channels between health insurance and relevant outcomes, there is a need to go beyond quantitative evidence alone, and combine the quantitative findings with qualitative insights. This is particularly important when we are trying to interpret some of the counterintuitive results encountered in the studies. This type of qualitative study should analyse the underlying socioeconomic and cultural drivers of low registration and non-usage of Indonesia's public health insurance scheme among informal sector workers. Since many studies have been conducted in the area of low CBHI enrolment in LMICs, the proposed qualitative study may also develop a theoretical framework based on those existing studies and look for more in-depth insights in the context of Indonesia. Considering the vast diversity of Indonesia, it is worth carrying out the qualitative study on several different large islands, at the very least.

Second, there is a need to develop more comprehensive measures of financial protection. Some authors have suggested certain alternatives, either by manipulating the standard health expenditure data from surveys (Moreno-Serra, Millet and Smith, 2011) or by collecting more comprehensive data from augmented survey questionnaires (Ruger, 2012). Future evaluation studies are encouraged to utilise more comprehensive measures to provide a more robust analysis of the effect of health insurance on financial protection.

Third, considering the greater effect of the JKN programme on the contributory group, there is a potential inequality as a side effect of its implementation. Future research needs to explore the extent to which the JKN programme closes or widens the gap of access to care and financial protection between the poorest and the most affluent.

Fourth, BPJS as the single payer has the potential to gather a sizeable amount of claim data which will allow researchers to predict the pattern of health expenditure and signs of moral hazard, especially for non-life-threatening conditions. Since rising health expenditure is likely to follow given the increased demand for the generous medical benefits of the JKN programme, BPJS should develop a more strategic approach to budget deficit prevention, informed by sound reasoning and robust evidence.



## Appendices

**Table A-1 Search strategies for the review of review in Chapter 4**

Databases	<b>Database of Abstracts and Reviews of Effect (DARE)</b>
Host	Centre for Reviews and Disseminations (CRD)
Date of search	01 December 2017
Years covered	1965 to December 2017
Search strategy	Any field: health insurance NOT cost-effectiveness
Language restrictions	None
Number of citations	284 records
Databases	<b>Cochrane Database of Systematic Reviews</b>
Host	Wiley online library
Date of search	07 March 2016
Years covered	1965 to March 2016
Search strategy	(all search terms are in title, abstract, and keywords)
	#1 ((developing next countr*) or ("low income" next countr*) or ("middle income"next countr*) or (under-developed next countr*) or (less-developed next countr*) or ("third world"next countr*))
	#2 MeSH descriptor Developing Countries explode all trees
	#3 MeSH descriptor Insurance, Health explode all trees
	#4 insurance
	#5 (#1 OR #2)
	#6 (#3 OR #4)
	#7 (#5 AND #6)
Language restrictions	None
Number of citations	198 records
Databases	<b>CINAHL Plus</b>
Host	EBSCO
Date of search	1 December 2017
Years covered	1965 to December 2017
Search strategy	S1 (MH "Insurance, Health+")
	S2 (MH "Prospective Payment System+")
	S3 TI health insurance
	S4 Health insurance
	S5 (MH "Insurance, Health, Reimbursement+")
	S6 (MH "Health Insurance Exchanges")
	S7 S1 OR S2 OR S3 OR S4 OR S5 OR S6
	S8 ("developing countr*" or "developing countr*" or "low income countr*" or "middle income countr*" or "under-developed countr*" or "less-developed countr*" or "third world countr*")
	S9 (MM "Developing Countries")
	S10 TI (Bangladesh or Benin or "Burkina Faso" or Burundi or "Central African Republic" or Chad or Comoros or Congo or Kongo or Eritrea or Ethiopia or Gambia or Guinea or "Guinea-Bissau" or Haiti or Kenya or Kyrgyz or Liberia or Madagascar or Malawi or Mali or Mozambique or Myanmar or Nepal or Niger or Rwanda or

S11 “Sierra Leone” or Somalia or Tajikistan or Tanzania or Togo or Uganda or Zimbabwe)  
 S12 TI (South Sudan or Kiribati or Lao or Samoa or “Solomon Islands” or “Timor Leste” or Tuvalu or Vanuatu or Afghanistan or Bhutan)  
 S13 TI (Armenia or Bolivia or Cameroon or “Cape Verde” or Congo or “Côte d’Ivoire” or Djibouti or Egypt or “El Salvador” or Georgia or Ghana or Guatemala or Guyana or Honduras or Indonesia or Lesotho or Mauritania or Moldova or Morocco or Nicaragua or Nigeria or Pakistan or “Papua New Guinea” or Paraguay or Philippines or “Sao Tome and Principe” or Senegal or “Sri Lanka” or Sudan or Syrian or Ukraine or Uzbekistan or Vietnam or Yemen or Zambia)  
 S14 TI (Albania or Algeria or Angola or Argentina or Azerbaijan or Belarus or “Bosnia and Herzegovina” or Botswana or Brazil or Bulgaria or China or Colombia or “Costa Rica” or Cuba or “Dominican Republic” or Ecuador or Gabon or Hungary or Iran or Iraq or Jamaica or Jordan or Kazakhstan or Lebanon or Libya or Malaysia or Mauritius or Mexico or Montenegro or Namibia or Panama or Peru or Romania or Serbia or “South Africa” or Thailand or Yugoslav or Macedonia or Tunisia or Turkey or Turkmenistan or Venezuela)  
 S15 S8 OR S9 OR S10 OR S11 OR S12 OR S13  
 S16 AB review\* OR TI review\*  
 S17 (MM "Systematic Review")  
 S18 (MM "Meta Analysis")  
 S19 S15 OR S16 OR S17  
 S19 S7 AND S14 AND S18

Language restrictions None

Number of citations 196

Databases **Econlit 1886 to 2017**

Host OvidSP

Date of search 1 December 2017

Years covered 1965 to December 2017

Search strategy

1. Developing Countries.kw.
2. (developing adj3 (countr\$ or nation or nations)).tw.
3. (under-developed adj3 (countr\$ or nation or nations)).tw.
4. (less-developed adj3 (countr\$ or nation or nations)).tw.
5. (third-world adj3 (countr\$ or nation or nations)).tw.
6. low income countr\$.tw.
7. middle income countr\$.tw.
8. or/1-7
9. (Albania or Algeria or Angola or Argentina or Azerbaijan or Belarus or Bosnia or Botswana or Brazil or Bulgaria or China or Colombia or Costa Rica or Cuba or Dominican Republic or Ecuador or Gabon or Hungary or Iran or Iraq or Jamaica or Jordan or Kazakhstan or Lebanon or Libya or Malaysia or Mauritius or Mexico or Montenegro or Namibia or Panama or Peru or Romania or Serbia or South Africa or Thailand or Yugoslav or Macedonia or Tunisia or Turkey or Turkmenistan or Venezuela).tw.
10. (Armenia or Bolivia or Cameroon or Cape Verde or Congo or Cote d Ivoire or Djibouti or Egypt or El Salvador or Georgia or Ghana or Guatemala or Guyana or Honduras or Indonesia or Lesotho or Mauritania or Moldova or Morocco or Nicaragua or Nigeria or Pakistan

or Papua New Guinea or Paraguay or Philippines or Sao Tome Principe or Senegal or Sri Lanka or Sudan or Syrian or Ukraine or Uzbekistan or Vietnam or Yemen or Zambia).tw.

11. (South Sudan or Kiribati or Lao or Samoa or Solomon Islands or Timor Leste or Tuvalu or Vanuatu or Afghanistan or Bhutan).tw.
12. (Bangladesh or Benin or Burkina Faso or Burundi or Central African Republic or Chad or Comoros or Congo or Kongo or Eritrea or Ethiopia or Gambia or Guinea or Guinea-Bissau or Haiti or Kenya or Kyrgyz or Liberia or Madagascar or Malawi or Mali or Mozambique or Myanmar or Nepal or Niger or Rwanda or Sierra Leone or Somalia or Tajikistan or Tanzania or Togo or Uganda or Zimbabwe).tw.
13. (africa or asia or "latin america and the caribbean").gr.
14. or/9-13
15. 8 or 14
16. insurance.mp. [mp=heading words, abstract, title, country as subject]
17. review\$.ab.
18. review\$.ti.
19. 21 or 22
20. 15 AND 16 AND 19

Language restrictions None

Number of citations 194 records

Databases **Embase 1974 to 2017**

Host OvidSP

Date of search 1 December 2017

Years covered 1965 to December 2017

Search strategy

- 1 Social Insurance/
- 2 Public Health Insurance/
- 3 National Health Insurance/
- 4 health insurance.ti.
- 5 (social adj5 insurance\$.tw.
- 6 (community adj5 insurance\$.tw.
- 7 (health insurance adj3 program\$.tw.
- 8 universal health insuranc\$.tw.
- 9 affordable health insuranc\$.tw.
- 10 (health insurance adj3 scheme\$.tw.
- 11 micro health insurance\$.tw.
- 12 or/1-11
- 13 Developing country/
- 14 (developing adj3 (countr\$ or nation or nations)).tw.
- 15 (under-developed adj3 (countr\$ or nation or nations)).tw.
- 16 (less-developed adj3 (countr\$ or nation or nations)).tw.
- 17 (third-world adj3 (countr\$ or nation or nations)).tw.
- 18 low income countr\$.tw.
- 19 middle income countr\$.tw.
- 20 or/13-19
- 20 exp Africa/
- 21 exp "South and Central America"/
- 22 Mexico/
- 23 exp Caribbean Islands/
- 24 exp Eastern Europe/
- 25 exp Pacific islands/
- 26 exp Southeast Asia/

- 27 exp south asia/  
 28 middle east/  
 29 china/  
 30 korea/  
 31 mongolia/  
 32 philippines/  
 33 taiwan/  
 34 iran/  
 35 iraq/  
 36 jordan/  
 37 lebanon/  
 38 palestine/  
 39 syrian arab republic/  
 40 "turkey (republic)"/  
 41 yemen/  
 42 asia/  
 43 kazakhstan/  
 44 kyrgyzstan/  
 45 tajikistan/  
 46 turkmenistan/  
 47 uzbekistan/  
 48 exp Indian Ocean/
49. (Albania or Algeria or Angola or Argentina or Azerbaijan or Belarus or Bosnia or Botswana or Brazil or Bulgaria or China or Colombia or Costa Rica or Cuba or Dominican Republic or Ecuador or Gabon or Hungary or Iran or Iraq or Jamaica or Jordan or Kazakhstan or Lebanon or Libya or Malaysia or Mauritius or Mexico or Montenegro or Namibia or Panama or Peru or Romania or Serbia or South Africa or Thailand or Yugoslav or Macedonia or Tunisia or Turkey or Turkmenistan or Venezuela).tw.
50. (Armenia or Bolivia or Cameroon or Cape Verde or Congo or Cote d'Ivoire or Djibouti or Egypt or El Salvador or Georgia or Ghana or Guatemala or Guyana or Honduras or Indonesia or Lesotho or Mauritania or Moldova or Morocco or Nicaragua or Nigeria or Pakistan or Papua New Guinea or Paraguay or Philippines or Sao Tome Principe or Senegal or Sri Lanka or Sudan or Syrian or Ukraine or Uzbekistan or Vietnam or Yemen or Zambia).tw.
51. (South Sudan or Kiribati or Lao or Samoa or Solomon Islands or Timor Leste or Tuvalu or Vanuatu or Afghanistan or Bhutan).tw.
52. (Bangladesh or Benin or Burkina Faso or Burundi or Central African Republic or Chad or Comoros or Congo or Kongo or Eritrea or Ethiopia or Gambia or Guinea or Guinea-Bissau or Haiti or Kenya or Kyrgyz or Liberia or Madagascar or Malawi or Mali or Mozambique or Myanmar or Nepal or Niger or Rwanda or Sierra Leone or Somalia or Tajikistan or Tanzania or Togo or Uganda or Zimbabwe).tw.
- 53 or/12-52  
 54 or/1-11  
 55 53 and 54
- 56 (((comprehensive\* or integrative or systematic\*) adj3 (bibliographic\* or review\* or literature)) or (meta-analy\* or metaanaly\* or "research synthesis" or ((information or data) adj3 synthesis) or (data adj2 extract\*))) .ti,ab. or (cinahl or (cochrane adj3 trial\*) or embase or medline or psyclit or (psycinfo not "psycinfo database") or pubmed or scopus or "sociological abstracts" or "web of science").ab. or

("cochrane database of systematic reviews" or evidence report technology assessment or evidence report technology assessment summary).jn. or Evidence Report: Technology Assessment\*.jn. or ((review adj5 (rationale or evidence)).ti,ab. and review.pt.) or meta-analysis as topic/ or Meta-Analysis.pt.

57 review\$.ab.  
 58 review\$.ti.  
 59 55 AND (56 OR 57 OR 58)

Language restrictions None  
 Number of citations 752

Databases **Ovid MEDLINE(R)**

Host OvidSP

Date of search 1 December 2017

Years covered 1965 to December 2017

Search strategy

- 1 Insurance, Health/
- 2 Insurance, Health, Reimbursement/
- 3 Insurance, Hospitalization/
- 4 Insurance, Major Medical/
- 5 Insurance, Physician Services/
- 6 Insurance, Surgical/
- 7 Single-Payer System/
- 8 exp Insurance Coverage/
- 9 health insurance.ti.
- 10 (social adj5 insurance\$.tw.
- 11 (community adj5 insurance\$.tw.
- 12 (health insurance adj3 program\$.tw.
- 13 universal health insuranc\$.tw.
- 14 affordable health insuranc\$.tw.
- 15 (health insurance adj3 scheme\$.tw.
- 16 micro health insurance\$.tw.
- 17 or/1-16
- 18 Developing Countries/
- 19 (developing adj3 (countr\$ or nation or nations)).tw.
- 20 (under-developed adj3 (countr\$ or nation or nations)).tw.
- 21 (less-developed adj3 (countr\$ or nation or nations)).tw.
- 22 (third-world adj3 (countr\$ or nation or nations)).tw.
- 23 low income countr\$.tw.
- 24 middle income countr\$.tw.
- 25 or/18-24
- 26 exp Africa/
- 27 exp South America/
- 28 exp Central America/
- 29 Mexico/
- 30 Latin America/
- 31 exp caribbean region/
- 32 exp Europe, Eastern/
- 33 pacific islands/
- 34 exp melanesia/
- 35 exp asia, central/
- 36 exp asia, southeastern/
- 37 exp asia, western/
- 38 exp china/
- 39 mongolia/



40 exp indian ocean islands/  
41 or/25-40  
42. (Albania or Algeria or Angola or Argentina or Azerbaijan or Belarus or Bosnia or Botswana or Brazil or Bulgaria or China or Colombia or Costa Rica or Cuba or Dominican Republic or Ecuador or Gabon or Hungary or Iran or Iraq or Jamaica or Jordan or Kazakhstan or Lebanon or Libya or Malaysia or Mauritius or Mexico or Montenegro or Namibia or Panama or Peru or Romania or Serbia or South Africa or Thailand or Yugoslav or Macedonia or Tunisia or Turkey or Turkmenistan or Venezuela).tw.  
43. (Armenia or Bolivia or Cameroon or Cape Verde or Congo or Cote d Ivoire or Djibouti or Egypt or El Salvador or Georgia or Ghana or Guatemala or Guyana or Honduras or Indonesia or Lesotho or Mauritania or Moldova or Morocco or Nicaragua or Nigeria or Pakistan or Papua New Guinea or Paraguay or Philippines or Sao Tome Principe or Senegal or Sri Lanka or Sudan or Syrian or Ukraine or Uzbekistan or Vietnam or Yemen or Zambia).tw.  
44. (South Sudan or Kiribati or Lao or Samoa or Solomon Islands or Timor Leste or Tuvalu or Vanuatu or Afghanistan or Bhutan).tw.  
45. (Bangladesh or Benin or Burkina Faso or Burundi or Central African Republic or Chad or Comoros or Congo or Kongo or Eritrea or Ethiopia or Gambia or Guinea or Guinea-Bissau or Haiti or Kenya or Kyrgyz or Liberia or Madagascar or Malawi or Mali or Mozambique or Myanmar or Nepal or Niger or Rwanda or Sierra Leone or Somalia or Tajikistan or Tanzania or Togo or Uganda or Zimbabwe).tw.  
46 42 or 43 or 44 or 45  
47 41 or 46  
48 17 and 47  
49 (((comprehensive\* or integrative or systematic\*) adj3 (bibliographic\* or review\* or literature)) or (meta-analy\* or metaanaly\* or "research synthesis" or ((information or data) adj3 synthesis) or (data adj2 extract\*))) .ti,ab. or (cinahl or (cochrane adj3 trial\*) or embase or medline or psyclit or (psycinfo not "psycinfo database") or pubmed or scopus or "sociological abstracts" or "web of science").ab. or ("cochrane database of systematic reviews" or evidence report technology assessment or evidence report technology assessment summary).jn. or Evidence Report: Technology Assessment\*.jn. or ((review adj5 (rationale or evidence)).ti,ab. and review.pt.) or meta-analysis as topic/ or Meta-Analysis.pt.  
50 review\$.ti.  
51 review\$.ab.  
52 49 OR 50 OR 51  
53 48 AND 52

Language restrictions None

Number of citations 442

Databases **Science Citation Index Expanded (SCI-EXPANDED)**  
**Social Sciences Citation Index (SSCI)**  
**Arts & Humanities Citation Index (A&HCI)**  
**Conference Proceedings Citation Index- Science (CPCI-S)**  
**Conference Proceedings Citation Index- Social Science & Humanities (CPCI-SSH)**

Host ISI Web of Science

Date of search 1 December 2017

Years covered 1965 to December 2017

Search strategy	<p>#1 ts=("developing countr*" or "developing countr*" or "low income countr*" or "middle income countr*" or "under-developed countr*" or "less-developed countr*" or "third world countr*")</p> <p>#2 TS=(Bangladesh or Benin or "Burkina Faso" or Burundi or "Central African Republic" or Chad or Comoros or Congo or Kongo or Eritrea or Ethiopia or Gambia or Guinea or "Guinea-Bissau" or Haiti or Kenya or Kyrgyz or Liberia or Madagascar or Malawi or Mali or Mozambique or Myanmar or Nepal or Niger or Rwanda or "Sierra Leone" or Somalia or Tajikistan or Tanzania or Togo or Uganda or Zimbabwe)</p> <p>#3 TS=( South Sudan or Kiribati or Lao or Samoa or "Solomon Islands" or "Timor Leste" or Tuvalu or Vanuatu or Afghanistan or Bhutan)</p> <p>#4 TS=(Armenia or Bolivia or Cameroon or "Cape Verde" or Congo or "Côte d'Ivoire" or Djibouti or Egypt or "El Salvador" or Georgia or Ghana or Guatemala or Guyana or Honduras or Indonesia or Lesotho or Mauritania or Moldova or Morocco or Nicaragua or Nigeria or Pakistan or "Papua New Guinea" or Paraguay or Philippines or "Sao Tome and Principe" or Senegal or "Sri Lanka" or Sudan or Syrian or Ukraine or Uzbekistan or Vietnam or Yemen or Zambia)</p> <p>#5 TS=(Albania or Algeria or Angola or Argentina or Azerbaijan or Belarus or "Bosnia and Herzegovina" or Botswana or Brazil or Bulgaria or China or Colombia or "Costa Rica" or Cuba or "Dominican Republic" or Ecuador or Gabon or Hungary or Iran or Iraq or Jamaica or Jordan or Kazakhstan or Lebanon or Libya or Malaysia or Mauritius or Mexico or Montenegro or Namibia or Panama or Peru or Romania or Serbia or "South Africa" or Thailand or Yugoslav or Macedonia or Tunisia or Turkey or Turkmenistan or Venezuela)</p> <p>#6 ts=(social same "health insurance" )</p> <p>#7 ts= (Community SAME "health insurance")</p> <p>#8 ti="health insurance"</p> <p>#9 ts=("health insurance" same scheme*)</p> <p>#10 ts=("health insurance" same program*)</p> <p>#11 ts="universal health insurance"</p> <p>#12 ts="affordable health insurance"</p> <p>#13 ts=(micro* same "health insurance")</p> <p>#14 ts=(public same "health insurance")</p> <p>#15 #6 or #7 or #8 or #9 or #10 or #11 or #12 or #13 or #14</p> <p>#16 #15 AND (#1 OR #2 OR #3 OR #4 OR #5)</p> <p>#17 TS=( review*)</p> <p>#18 #16 AND #17</p>
Language restrictions	None
Number of citations	284

**Table A-2. Search strategies for the updated review in Chapter 5**

Databases	<b>CINAHL Plus</b>
Host	EBSCO
Date of search	8 September 2016
Years covered	January 2010 to September 2016
Search strategy	S17 S15 AND S16 S16 Limiters to 2010-2016 S15 S7 AND S14 S14 S8 OR S9 OR S10 OR S11 OR S12 OR S13 S13 TI (Albania or Algeria or Angola or Argentina or Azerbaijan or Belarus or “Bosnia and Herzegovina” or Botswana or Brazil or Bulgaria or China or Colombia or “Costa Rica” or Cuba or “Dominican Republic” or Ecuador or Gabon or Hungary or Iran or Iraq or Jamaica or Jordan or Kazakhstan or Lebanon or Libya or Malaysia or Mauritius or Mexico or Montenegro or Namibia or Panama or Peru or Romania or Serbia or “South Africa” or Thailand or Yugoslav or Macedonia or Tunisia or Turkey or Turkmenistan or Venezuela S12 TI (Armenia or Bolivia or Cameroon or “Cape Verde” or Congo or “Côte d’Ivoire” or Djibouti or Egypt or “El Salvador” or Georgia or Ghana or Guatemala or Guyana or Honduras or Indonesia or Lesotho or Mauritania or Moldova or Morocco or Nicaragua or Nigeria or Pakistan or “Papua New Guinea” or Paraguay or Philippines or “Sao Tome and Principe” or Senegal or “Sri Lanka” or Sudan or Syrian or Ukraine or Uzbekistan or Vietnam or Yemen or Zambia) S11 TI (South Sudan or Kiribati or Lao or Samoa or “Solomon Islands” or “Timor Leste” or Tuvalu or Vanuatu or Afghanistan or Bhutan) S10 TI (Bangladesh or Benin or “Burkina Faso” or Burundi or “Central African Republic” or Chad or Comoros or Congo or Kongo or Eritrea or Ethiopia or Gambia or Guinea or “Guinea-Bissau” or Haiti or Kenya or Kyrgyz or Liberia or Madagascar or Malawi or Mali or Mozambique or Myanmar or Nepal or Niger or Rwanda or “Sierra Leone” or Somalia or Tajikistan or Tanzania or Togo or Uganda or Zimbabwe) S9 (MM “Developing Countries”) S8 (“developing countr*” or “developing countr*” or “low income countr*” or “middle income countr*” or “under-developed countr*” or “less-developed countr*” or “third world countr*”) S7 S1 OR S2 OR S3 OR S4 OR S5 OR S6 S6 (MH “Insurance, Health, Reimbursement+”) S5 (MH “Insurance, Health, Reimbursement+”) S4 Health insurance S3 TI health insurance S2 (MH “Prospective Payment System+”) S1 (MM “Insurance, Health+”)
Language restrictions	None
Number of citations	839

Databases	<b>Econlit 1886 to September 2015,</b>
Host	OvidSP
Date of search	8 September 2016
Years covered	2010 to September 2016
Search strategy	1 Health Insurance.kw. 2 health insurance.ti. 3 (social adj5 insurance\$.tw. 4 (community adj5 insurance\$.tw. 5 (health insurance adj3 program\$.tw. 6 universal health insuranc\$.tw. 7 affordable health insuranc\$.tw.

8 (health insurance adj3 scheme\$.tw.  
9 micro health insurance\$.tw.  
10 or/1-9  
11 Developing Countries.kw.  
12 (developing adj3 (countr\$ or nation or nations)).tw.  
13 (under-developed adj3 (countr\$ or nation or nations)).tw.  
14 (less-developed adj3 (countr\$ or nation or nations)).tw.  
15 (third-world adj3 (countr\$ or nation or nations)).tw.  
16 low income countr\$.tw.  
17 middle income countr\$.tw.  
18 or/11-17  
19 (Afghanistan or Guinea-Bissau or Rwanda or Bangladesh or Haiti or Senegal or Benin or Kenya or Sierra Leone or Burkina Faso or Korea or Somalia or Burundi or Kyrgyz Republic or Tajikistan or Cambodia or Lao or Tanzania or Central African Republic or Liberia or Togo or Chad or Madagascar or Uganda or Comoros or Malawi or Uzbekistan or Congo or Mali or Vietnam or Eritrea or Mauritania or Yemen or Ethiopia or Mozambique or Zambia or Gambia or Myanmar or Zimbabwe or Ghana or Nepal or Guinea or Niger).tw.  
20 (Albania or Honduras or Paraguay or Angola or India or Philippines or Armenia or Indonesia or Samoa or Azerbaijan or Iran or Sao Tome or Belize or Iraq or Solomon Islands or Bhutan or Jordan or Sri Lanka or Bolivia or Kiribati or Sudan or Cameroon or Kosovo or Swaziland or Cape Verde or Lesotho or Syria\$ or China or Maldives or Thailand or Congo or Marshall Islands or Timor-Leste).tw.  
21 (Micronesia or Tonga or Djibouti or Moldova or Tunisia or Ecuador or Mongolia or Turkmenistan or Egypt or Morocco or Ukraine or El Salvador or Nicaragua or Vanuatu or Georgia or Nigeria or Gaza or Guatemala or Pakistan or Guyana or Papua New Guinea or "West Bank" or Cote D'Ivoire).tw.  
22 (Algeria or Grenada or Peru or Samoa or Jamaica or Poland or Argentina or Kazakhstan or Romania or Belarus or Latvia or Russian Federation or Bosnia or Herzegovina or Lebanon or Serbia or Botswana or Libya or Seychelles or Brazil or Lithuania or South Africa or Bulgaria or Macedonia or St Kitts or Chile or Malaysia or St Lucia or Colombia or Mauritius or St Vincent or Grenadines or Costa Rica or Mayotte or Suriname or Cuba or Mexico or Turkey or Dominica or Montenegro or Uruguay or Dominican Republic or Namibia or Venezuela or Fiji or Palau or Gabon or Panama).tw.  
23 (afghanistan or africa or albania or algeria or angola or antigua or antilles or arab countries or argentina or armenia or asia or asia pacific or azerbaijan or balkans or bangladesh or belarus or belize or benin or bhutan or bolivia or bosnia herzegovina or botswana or brazil or bulgaria or burkina faso or burundi or cambodia or cameroon or caribbean or central africa or central african republic or central america or central asia or chile or china or colombia or congo or costa rica or croatia or cuba).ct.  
24 ("democratic republic of the congo" or developing countries or djibouti or dominica or dominican republic or e africa or e asia or e europe or ecuador or egypt or el salvador or eritrea or ethiopia or fiji or gabon or gambia or georgia or ghana or grenada or guatemala or guinea or guinea bissau or guyana or haiti or honduras or india or indonesia or iran or iraq or ivory coast or jamaica or jordan).ct.  
25 (kazakhstan or kenya or kiribati or korea or kyrgyzstan or laos or latin america or lebanon or lesotho or liberia or libya or macedonia or madagascar or maghreb or malawi or malaysia or maldives or mali or marshall islands or martinique or mauritania or mauritius or melanesia or mexico or micronesia or middle east or mongolia or morocco or

mozambique or myanmar or n africa or n korea or namibia or ne asia or nepal or nicaragua or niger or nigeria or oceania or pacific islands or pakistan or palestine or panama or papua new guinea or paraguay or peru or philippines or polynesia or puerto rico).ct.

26 (syria or tajikistan or tanzania or thailand or timor leste or tobago or togo or tonga or trinidad or "trinidad and tobago" or tunisia or turkey or turkmenistan or uganda or ukraine or uruguay or ussr or uzbekistan or vanuatu or venezuela or vietnam or w africa or w indies or yemen or zambia or zimbabwe).ct.

27 (africa or asia or "latin america and the caribbean").gr.

28 or/19-27

29 18 or 28

30 10 and 29

31 Limit 30 to yr ="2010-Current"

Language restrictions None  
Number of citations 486 records

Databases **Embase 1974 to 2016 September,**

Host OvidSP

Date of search 8 September 2016

Years covered 2010 to September 2016

Search strategy  
1 Social Insurance/  
2 Public Health Insurance/  
3 National Health Insurance/  
4 health insurance.ti.  
5 (social adj5 insurance\$.tw.  
6 (community adj5 insurance\$.tw.  
7 (health insurance adj3 program\$.tw.  
8 universal health insuranc\$.tw.  
9 affordable health insuranc\$.tw.  
10 (health insurance adj3 scheme\$.tw.  
11 micro health insurance\$.tw.  
12 or/1-11  
13 Developing country/  
14 (developing adj3 (countr\$ or nation or nations)).tw.  
15 (under-developed adj3 (countr\$ or nation or nations)).tw.  
16 (less-developed adj3 (countr\$ or nation or nations)).tw.  
17 (third-world adj3 (countr\$ or nation or nations)).tw.  
18 low income countr\$.tw.  
19 middle income countr\$.tw.  
20 or/13-19  
20 exp Africa/  
21 exp "South and Central America"/  
22 Mexico/  
23 exp Caribbean Islands/  
24 exp Eastern Europe/  
25 exp Pacific islands/  
26 exp Southeast Asia/  
27 exp south asia/  
28 middle east/  
29 china/  
30 korea/  
31 mongolia/

32 philippines/  
 33 taiwan/  
 34 iran/  
 35 iraq/  
 36 jordan/  
 37 lebanon/  
 38 palestine/  
 39 syrian arab republic/  
 40 "turkey (republic)"/  
 41 yemen/  
 42 asia/  
 43 kazakhstan/  
 44 kyrgyzstan/  
 45 tajikistan/  
 46 turkmenistan/  
 47 uzbekistan/  
 48 exp Indian Ocean/  
 49 (Afghanistan or Guinea-Bissau or Rwanda or Bangladesh or Haiti or Senegal or Benin or Kenya or Sierra Leone or Burkina Faso or Korea or Somalia or Burundi or Kyrgyz Republic or Tajikistan or Cambodia or Lao or Tanzania or Central African Republic or Liberia or Togo or Chad or Madagascar or Uganda or Comoros or Malawi or Uzbekistan or Congo or Mali or Vietnam or Eritrea or Mauritania or Yemen or Ethiopia or Mozambique or Zambia or Gambia or Myanmar or Zimbabwe or Ghana or Nepal or Guinea or Niger).tw.  
 50 (Albania or Honduras or Paraguay or Angola or India or Philippines or Armenia or Indonesia or Samoa or Azerbaijan or Iran or Sao Tome or Belize or Iraq or Solomon Islands or Bhutan or Jordan or Sri Lanka or Bolivia or Kiribati or Sudan or Cameroon or Kosovo or Swaziland or Cape Verde or Lesotho or Syria\$ or China or Maldives or Thailand or Congo or Marshall Islands or Timor-Leste).tw.  
 51 (Micronesia or Tonga or Djibouti or Moldova or Tunisia or Ecuador or Mongolia or Turkmenistan or Egypt or Morocco or Ukraine or El Salvador or Nicaragua or Vanuatu or Georgia or Nigeria or Gaza or Guatemala or Pakistan or Guyana or Papua New Guinea or "West Bank" or Cote D'Ivoire).tw.  
 52 (Algeria or Grenada or Peru or Samoa or Jamaica or Poland or Argentina or Kazakhstan or Romania or Belarus or Latvia or Russian Federation or Bosnia or Herzegovina or Lebanon or Serbia or Botswana or Libya or Seychelles or Brazil or Lithuania or South Africa or Bulgaria or Macedonia or St Kitts or Chile or Malaysia or St Lucia or Colombia or Mauritius or St Vincent or Grenadines or Costa Rica or Mayotte or Suriname or Cuba or Mexico or Turkey or Dominica or Montenegro or Uruguay or Dominican Republic or Namibia or Venezuela or Fiji or Palau or Gabon or Panama).tw.  
 53 or/12-52  
 54 or/1-11  
 55 53 and 54  
 56 limit 55 to yr="2010 -Current"

Language restrictions None  
 Number of citations 3913 records

Databases **Ovid MEDLINE(R)**

Host	OvidSP
Date of search	8 September 2016
Years covered	January 2010 to September 2016
Search strategy	<p>1 Insurance, Health/  2 Insurance, Health, Reimbursement/  3 Insurance, Hospitalization/  4 Insurance, Major Medical/  5 Insurance, Physician Services/  6 Insurance, Surgical/  7 Single-Payer System/  8 exp Insurance Coverage/  9 health insurance.ti.  10 (social adj5 insurance\$.tw.  11 (community adj5 insurance\$.tw.  12 (health insurance adj3 program\$.tw.  13 universal health insuranc\$.tw.  14 affordable health insuranc\$.tw.  15 (health insurance adj3 scheme\$.tw.  16 micro health insurance\$.tw.  17 or/1-16  18 Developing Countries/  19 (developing adj3 (countr\$ or nation or nations)).tw.  20 (under-developed adj3 (countr\$ or nation or nations)).tw.  21 (less-developed adj3 (countr\$ or nation or nations)).tw.  22 (third-world adj3 (countr\$ or nation or nations)).tw.  23 low income countr\$.tw.  24 middle income countr\$.tw.  25 or/18-24  26 exp Africa/  27 exp South America/  28 exp Central America/  29 Mexico/  30 Latin America/  31 exp caribbean region/  32 exp Europe, Eastern/  33 pacific islands/  34 exp melanesia/  35 exp asia, central/  36 exp asia, southeastern/  37 exp asia, western/  38 exp china/  39 mongolia/  40 exp indian ocean islands/  41 or/25-40  42 (Afghanistan or Guinea-Bissau or Rwanda or Bangladesh or Haiti or Senegal or Benin or Kenya or Sierra Leone or Burkina Faso or Korea or Somalia or Burundi or Kyrgyz Republic or Tajikistan or Cambodia or Lao or Tanzania or Central African Republic or Liberia or Togo or Chad or Madagascar or Uganda or Comoros or Malawi or Uzbekistan or Congo or Mali or Vietnam or Eritrea or Mauritania or Yemen or Ethiopia or Mozambique or Zambia or Gambia or Myanmar or Zimbabwe or Ghana or Nepal or Guinea or Niger).tw.  43 (Albania or Honduras or Paraguay or Angola or India or Philippines or Armenia or Indonesia or Samoa or Azerbaijan or Iran or Sao Tome or Belize or Iraq or Solomon Islands or Bhutan or Jordan or Sri Lanka or Bolivia or Kiribati or Sudan or Cameroon or Kosovo or Swaziland or Cape</p>

Verde or Lesotho or Syria\$ or China or Maldives or Thailand or Congo or Marshall Islands or Timor-Leste).tw.

44 (Micronesia or Tonga or Djibouti or Moldova or Tunisia or Ecuador or Mongolia or Turkmenistan or Egypt or Morocco or Ukraine or El Salvador or Nicaragua or Vanuatu or Georgia or Nigeria or Gaza or Guatemala or Pakistan or Guyana or Papua New Guinea or "West Bank" or Cote Divoire).tw.

45 (Algeria or Grenada or Peru or Samoa or Jamaica or Poland or Argentina or Kazakhstan or Romania or Belarus or Latvia or Russian Federation or Bosnia or Herzegovina or Lebanon or Serbia or Botswana or Libya or Seychelles or Brazil or Lithuania or South Africa or Bulgaria or Macedonia or St Kitts or Chile or Malaysia or St Lucia or Colombia or Mauritius or St Vincent or Grenadines or Costa Rica or Mayotte or Suriname or Cuba or Mexico or Turkey or Dominica or Montenegro or Uruguay or Dominican Republic or Namibia or Venezuela or Fiji or Palau or Gabon or Panama).tw.

46 42 or 43 or 44 or 45

47 41 or 46

48 17 and 47

49 Limit 48 to yr="2010-Current"

Language restrictions None  
Number of citations 1963

Databases **Science Citation Index Expanded (SCI-EXPANDED)**  
**Social Sciences Citation Index (SSCI)**  
**Arts & Humanities Citation Index (A&HCI)**  
**Conference Proceedings Citation Index- Science (CPCI-S)**  
**Conference Proceedings Citation Index- Social Science & Humanities (CPCI-SSH)**

Host ISI Web of Science

Date of search 8 September 2016

Years covered January 2010 to September 2016

Search strategy #21 #16 or #17 or #18 or #19 or #20

#20 #15 AND #5

#19 #15 AND #4

#18 #15 AND #3

#17 #15 AND #2

#16 #15 AND #1

#15 #6 or #7 or #8 or #9 or #10 or #11 or #12 or #13 or #14

#14 ts=(public same "health insurance")

#13 ts=(micro\* same "health insurance")

#12 ts="affordable health insurance"

#11 ts="universal health insurance"

#10 ts=("health insurance" same program\*)

#9 ts=("health insurance" same scheme\*)

#8 ti="health insurance"

#7 ts= (Community SAME "health insurance")

#6 ts=(social same "health insurance" )

#5 TS=(Algeria or Grenada or Peru or Samoa or Jamaica or Poland or Argentina or Kazakhstan or Romania or Belarus or Latvia or Russia or Bosnia or Herzegovina or Lebanon or Serbia or Botswana or Libya or Seychelles or Brazil or Lithuania or Africa or Bulgaria or Macedonia or "St Kitts" or Chile or Malaysia or "St Lucia" or Colombia or Mauritius or "St Vincent" or Grenadines or "Costa Rica" or Mayotte or Suriname or Cuba



or Mexico or Turkey or Dominica or Montenegro or Uruguay or "Dominican Republic" or Namibia or Venezuela or Fiji or Palau or Gabon or Panama)

#4 TS=(Albania or Honduras or Paraguay or Angola or India or Philippines or Armenia or Indonesia or Samoa or Azerbaijan or Iran or "Sao Tome" or Belize or Iraq or "Solomon Islands" or Bhutan or Jordan or "Sri Lanka" or Bolivia or Kiribati or Sudan or Cameroon or Kosovo or Swaziland or "Cape Verde" or Lesotho or Syria\* or China or Maldives or Thailand or Congo or "Marshall Islands" or Timor-Leste)

#3 TS=(Micronesia or Tonga or Djibouti or Moldova or Tunisia or Ecuador or Mongolia or Turkmenistan or Egypt or Morocco or Ukraine or "El Salvador" or Nicaragua or Vanuatu or Georgia or Nigeria or Gaza or Guatemala or Pakistan or Guyana or "Papua New Guinea" or "West Bank" or Cote DIvoire)

#2 TS=(Afghanistan or Guinea-Bissau or Rwanda or Bangladesh or Haiti or Senegal or Benin or Kenya or "Sierra Leone" or "Burkina Faso" or Korea or Somalia or Burundi or Kyrgyz or Tajikistan or Cambodia or Lao or Tanzania or "Central African Republic" or Liberia or Togo or Chad or Madagascar or Uganda or Comoros or Malawi or Uzbekistan or Congo or Mali or Vietnam or Eritrea or Mauritania or Yemen or Ethiopia or Mozambique or Zambia or Gambia or Myanmar or Zimbabwe or Ghana or Nepal or Guinea or Niger)

#1 TS=("developing countr\*" or "developing countr\*" or "low income countr\*" or "middle income countr\*" or "under-developed countr\*" or "less-developed countr\*" or "third world countr\*")

Language restrictions	None
Number of citations	1313 records

## **A-3 Detailed questionnaire of quality of effectiveness estimates from non-randomised studies QuEENS**

### **General issues (Questions 1-5)**

#### ***Question 1. Have different methods been compared within the study?***

It is reasonable for any study attempting to estimate treatment effects to implement a number of methods based on different assumptions. This could be used to gauge the sensitivity of the results to the assumptions underpinning the models. At the same time, adopting a number of approaches forces the analyst to think about the assumptions embedded in each of the methods and their plausibility and helps focus on those of most importance. However, different methods might be estimating different treatment parameters and therefore different numerical parameters might be the result of this. The possible answers to the above question are as follows:

(a) Yes

Results from methods which assume selection on observables are contrasted with other methods, including those assuming selection on unobservables.

(b) Partially

Results from different methods are contrasted but all the methods rely on the same assumption about selection, either selection on observables or selection on unobservables.

(c) No.

#### ***Question 2. Have the results of the study been compared to others in the literature?***

Similar to Question 1 above, a study should compare its results to those found in the literature. Given that they would relate to different methods and/or different datasets, one would expect differences in the results but consistency between them (or inconsistencies that are easily explained) will give credibility to the results. The possible answers here are:

(a) Yes, compared to alternative methods using the same dataset.

(b) Yes, compared to similar methods using other data sources.

(c) Not compared – no other estimates found in the literature. This option should be selected when there is an indication that a search was conducted in the literature but no other related estimates were found.

(d) Not compared.

#### ***Question 3. Is there a discussion of what treatment effect is identified and of the assumptions needed?***

Usually the parameter of interest in economic evaluations for NICE is the ATE but in some cases it might be the ATT. The parameter of interest in the analysis should match the parameter of interest in the economic evaluation. In Section 2, the different types of treatment effects that can be identified were discussed and were related to the different approaches and their assumptions. Any study should show an awareness of this issue. For example, if one is willing to make the assumption of homogeneity in the treatment effect, then it is straightforward to identify the ATE. With heterogeneity, the ATT might be identified under weak assumptions. However, the ATE may need a much more stringent set of assumptions. If the parameter of interest is the ATT, this is not a problem. A good study should justify how the estimated treatment effect related to the treatment effect of interest, together with their underpinning assumptions. The possible options to be selected are as follows:

- (a) Discussion of effect and assumptions.
- (b) Discussion of effect but not the assumptions.
- (c) Discussion of the assumptions but not the effect.
- (d) No discussion of either.

**Question 4: Is the model chosen consistent with the outcome variable if using a parametric method?**

The distribution of the outcome variable should inform the choice of the type of regression model to use. For example probit/logit models can be used with binary outcomes, generalised linear models can be very useful in cases where the data is highly skewed, etc. The possible options to be selected are as follows:

- (a) Yes
- (b) Unclear
- (c) No

**Question 5: Were any checks conducted on the model specification?**

Specification checks should be conducted on the models. The appropriate checks will depend on the model used. For example linear regression models can be assessed using plots of the residuals or more formally using misspecification, heteroskedasticity, autocorrelation, normality, etc. tests based on the residuals; if using kernel regression or matching it is important to check the sensitivity of the results to the choice of bandwidth and matching algorithm respectively (see Wooldridge, Jones and Rice, Kreif *et al.* 14,15,57). The possible options to be selected are as follows:

- (a) Yes, appropriate (detail which)
- (b) Yes, but inappropriate or not enough
- (c) No checks reported

**Methods assuming selection on observables (Questions 6-8)**

**Question 6. On selection: Is the assumption of selection on observables assessed?**

The methods presented in Section 2.2 are based on the assumption that selection is on observables. Strictly speaking, selection is on both observables and unobservables but the unobservables are not correlated with the outcomes and thus, their presence does not induce confounding. This assumption is often controversial and cannot be tested directly although placebo tests can sometimes be used. A convincing argument should put forward to substantiate the claim that the selected variables are sufficient and, once used in the analysis, there are no remaining unobserved variables affecting both the treatment and the outcome. The following options are available:

(a) Yes, expert literature/opinion cited. The analyst justifies the assumption with reference to *a priori* knowledge in the expert literature or if this is lacking with reference to expert opinion. Sometimes it is possible to assess this assumption indirectly by testing if a treatment effect is zero when it is known that it is. For example, if there is access to two different control groups, one can check that the treatment effect is zero between the two groups or one can use a variable known not to have an effect to estimate the treatment effect.

(b) Yes, theoretical reasoning given. The analyst justifies the assumption with a sensible theoretical argument but does not refer to the literature.

- (c) No.

**Question 7. What checks were conducted to assess overlap?**

All methods assuming selection on unobservables rely on good overlap in the distribution of the covariates between the treatment and control groups. Even if ignorability holds, the results will be suspect if there is lack of overlap between the treatment and control groups. Lack of overlap implies that regression estimates extrapolate to regions well outside the sample, might cause instability in estimates using IPW and call into question matching estimates of the average treatment effect as it will not be possible to find matches for some individuals.

(a) Yes, thorough checks. As a starting point, it is useful to report normalised differences in covariates for the treatment and the control groups to check if overlap is a problem. Normalised differences above 0.25 have been suggested as signalling problems with overlap. It is important to emphasise that normalised differences are different from the usual t-statistics of the difference in means between the treatment and control groups. Looking at one covariate at a time and focusing only on one moment (the mean) in its distribution is insufficient. Other more thorough checks include comparing histograms or kernel plots of the covariates for the treatment and the control groups, quantile-quantile (QQ) plots, higher moments and cross moments of covariate distributions. If there are many covariates or the propensity score is estimated as part of the model, a better alternative is to present distributions of the propensity score by treatment group because we are trying to assess if there are any areas where the density of the covariates is zero for one group and non-zero for the other. Note that the overlap in the covariates will most likely be assessed as part of a nonparametric regression method for example.

(b) Yes, minimum checks. These include normalised differences at the very least and perhaps some but not all of the additional checks reported in (a).

(c) No checks reported.

**Question 8: Has balancing of the covariates been checked after matching and propensity score methods?**

Matching and propensity score methods should achieve balancing of the covariates.

(a) Yes, minimum checks. The analyst can use normalised differences appropriate for each methods in covariates for the treatment and the control groups or weighted normalised differences in the case of IPW as in Austin.<sup>45</sup>

(b) Yes, more thorough checks. Other more thorough checks include comparing histograms or kernel plots of the covariates for the treatment and the control groups, or if matching on the propensity score comparing distributions of the propensity score by treatment.

(c) No checks reported.

**Methods using the propensity score (Questions 9-10)**

**Question 9: Is the propensity score function sufficiently flexible?**

It has been suggested that the propensity score function needs to be sufficiently flexible and therefore should include not just the variables in levels but also squares and interactions. Clearly, the flexibility will depend on the size of the dataset. One can also use semiparametric/non-parametric functions to model the propensity score. The available choices for this question are:

(a) Yes, includes interactions or different functions of the covariates

(b) Yes, flexible due to semiparametric/non-parametric specification

(c) Unlikely to be flexible enough

(d) Unclear or not reported

**Question 10: Are potential IVs excluded from the set of conditioning variables?**

Variables that should be included in the conditioning set are variables measured before the assignment to treatment takes place, including past outcomes. Variables that are potential IVs should not be included because they have been shown to increase the bias in matching type estimators unless they are exogenous. Even in this case, when they do not cause a bias, they will increase the asymptotic variance of the estimate. The available choices are:

- (a) Yes
- (b) Some variables might present a problem
- (c) IV clearly included

**Matching methods (Questions 11-14)**

**Question 11: Are there data quality issues?**

An important issue in matching is the quality of the data. For the treatment effect calculated using matching to be convincing, the data and the definitions for the treated and control groups must be comparable. The assumption of no unobserved confounders remaining which affect both the treatment and the outcome is more compelling if the treated and controls come from the same, or at least very similar, environment. It is also important that the dataset includes a good number of variables that can be used for matching and that the sample sizes before matching are big enough so there are plenty of potential matches. Accordingly, the following subcategories are available:

- (a) Data and definitions comparable for treated and control groups: Yes/No/Unclear or not reported.
- (b) Treated and control come from the same area or environment: Yes/No/Unclear or not reported.
- (c) Rich set of variables: Yes, available and used/Not available or not used.
- (d) Reasonable sample sizes: Yes, likely/ No.

**Question 12: For Nearest Neighbour matching: Has bias adjustment been conducted if more than one variable was included?**

Abadie and Imbens<sup>61,62</sup> showed that the estimator obtained using Nearest Neighbour matching is biased if matching on more than one continuous covariate and proposed a bias adjustment. Imbens and Wooldridge<sup>13</sup> highlight the cases under which the bias will be small in practice.

- (a) Yes
- (b) No

**Question 13: Is the choice of replacement (with/without) reasonable?**

Matching without replacement if the control group is small might result in bad matches which increase the bias of the estimator. Matching with replacement might result in the same individuals in the control group being matched to in areas of the propensity score where there are many more treated observations than controls. This means that some untreated individuals may be matched repeatedly. One of the following options should be selected:

- (a) Yes
- (b) Likely
- (c) No

**Question 14: Is the choice of the number of matches/caliper matching/radius matching reasonable?**

There is a trade-off between bias and variance which the analyst needs to take into account. Note that this is a subjective decision and there is not much known about, for example, how to select the number of matches.

- (a) Yes
- (b) Likely
- (c) No

**IV methods (Questions 15-18)**

**Question 15: Is the instrument well justified?**

An IV variable needs to affect the treatment directly but the outcome only indirectly through its effect on the treatment. This exclusion restriction is key but cannot be tested directly. If there is more than one IV, one can test over-identifying restrictions (see Question 17) but in most cases one needs to rely on the published literature and expert opinion.

- (a) Yes, theoretically
- (b) Yes, citing expert literature
- (c) No

**Question 16: Is the sample size relatively large?**

IV methods are biased on finite samples but they are consistent in large samples. Therefore it is important that they are used in relatively large datasets.

- (a) Yes
- (b) No

**Question 17: If more than one IV, is the test of over-identifying restrictions reported?**

A test of over-identifying restrictions is essentially a test of instrument validity and should be reported whenever there are more instruments than endogenous variables. If the number of endogenous variables is the same as the number of instruments, one can always create additional instruments by interacting the IV with other covariates in the model. Note that rejection of the hypothesis could be due to a failure of the instrument but also to model misspecification.

- (a) Yes
- (b) No

**Question 18: Is a weak instrument(s) test reported?**

Weak instruments lead to an increase in the bias of the estimator. Simple correlations or partial correlations can be used in the first instance. More formal tests such as that reported in Cragg and Donald<sup>63</sup> could also be used.

- (a) Yes
- (b) No

**Difference in Differences (Questions 20-23)**

The following sets of questions relate to assumptions that are untestable and it is therefore important that the analyst justifies them with reference to the published literature or expert opinion.

**Question 20: Does the intervention generate exogenous variation? (not applicable if natural experiment)**

The DiD approach makes use of interventions or events which induce random assignment of the individual to the treatment and control groups or at least random eligibility. This is similar to the exogenous variation in the treatment variable achieved by randomisation. In general, this is not applicable for natural experiments although it is always appropriate to assess if the natural experiment generated exogenous variation.

- (a) Yes, highly likely
- (b) Unlikely
- (c) Not applicable

**Question 21: Is the assumption of common trends across groups reasonable?**

Differential trends might arise if for example, the treatment and control groups are based in different areas with different trends in the outcomes, or when external shocks to the outcome happen at different time points. The differential trend adjusted DID estimator can be used if the trends might not be the same and the analyst has access to historical data (see Section 2.5.1).

- (a) Yes, highly likely
- (b) Unlikely

**Question 22: Is it reasonable to assume that there is no selection of unobserved temporary individual specific shocks?**

This question relates to the Ashenfelter's dip discussed in the previous section. If individuals are able to change their behaviour before the timing of the treatment to manipulate their probability of getting the treatment, the DID method will not be able to identify the correct treatment effect.

- (a) Yes, highly likely
- (b) Unlikely

**Question 23: Is the assumption of no systematic composition changes within each group reasonable? (applicable with repeated cross-sections, not with longitudinal data)**

The DiD method is able to remove the unobserved individual effect using repeated cross-sections only if there are no composition changes in the groups so that the average unobserved individual effect remains the same before and after the treatment or intervention.

- (a) Yes, highly likely
- (b) Unlikely
- (c) Not applicable

**Regression Discontinuity Design (Questions 24-25)**

**Question 24: Is the sample size relatively large?**

In common with IV methods, the regression discontinuity design identifies a local parameter and therefore the estimates may not be very precise if the sample size is small.

- (a) Yes
- (b) No

**Question 25: Is the assumption that individuals are not able to affect the instrument to change the likelihood of participation reasonable?**

The regression discontinuity design will in general not be able to identify the required treatment effect if individuals are able to manipulate the instrument to increase/decrease their likelihood of participation. In this case, individuals below and above the threshold are different in terms of the unobservables.

- (a) Yes
- (b) No



**Table A-4 Summary of all included studies (N = 68)**

ID	Study	Type of Study	QUEENS	GRADE	Utilisation	Financial Protection	Health Outcomes
1	Babiarz et al (2010). Country: China. Scheme: SHI	Difference in difference (DID). Data: Household Survey. N=6,201	2	Low	5% increase in village clinics use, but no change in overall medical care use.	OOP spending fell by 19%, 2%-point reduction in the likelihood of catastrophic health expenditure and 2%-point reduction in the likelihood of financing medical care through asset sales or borrowing	
2	Galarraga et al. (2010). Country: Mexico. Scheme: SHI	Instrumental variables (IV), bivariate probit, and two-stage residual inclusion (2SRI). Data: Household survey. N=20,792	2	Low		SP Impact Survey: Outpatients expenses decreased by \$447; hospitalization by \$450; and medicines by \$111 pesos per year. Reduced Catastrophic health expenditure event by 4.6 % points with bivariate probit and 4.7 % points with 2SRI. ENSANUT: Conclusion is similar, but lower magnitude. 171; 175; 360; 3.6; 3.7	
3	Koch and Alaba (2010). Country: South Africa. Scheme: SHI	Propensity score matching (PSM). Data: Household survey. N=4,780	1	Low		The analysis suggests that rural households would accommodate the increased insurance burden by either decreasing other food expenditures by about 20% or by decreasing their transportation and communication budgets by about 15%. Similar result for urban population	
4	Trujillo et al. (2010). Country: Colombia. Scheme: SHI	IV. Data: Household survey. N=1,438	1	Low	People in contributory system were 25.9 percent more likely to report use of preventive visits compared with people in subsidized system. People in subsidized system is not likely to take preventive effort compared with uninsured population. Ex ante moral hazard is suggested		
5	Hou and Chao (2011) Country: Georgia Scheme: SHI	Regression Discontinuity (RD) and two-part model (2PM) Data: Administrative data N: 29460	3	Medium	MIP beneficiaries are nine time more likely to utilize acute surgeries compared to non-MIP beneficiaries. The poorest are 47% more likely to have acute surgery compared than the richest and 13% more likely to have planned surgeries. No significant difference for baby deliveries		

6	Panpiemras et al. (2011). Country: Thailand. Scheme: SHI	Fixed effect (FE). Data: Household survey. N=63360	1	Low	The number of outpatients increased by 55.98% while the outpatient visits increased by 41.34% after the UC program was implemented. However, similar results were not found for inpatients. The effect of the UC program faded away quickly in the subsequent years.	
7	Quimbo et al. (2011) Country: The Philippines Scheme: SHI	DID. Data: Randomised study. N = 1100	3	Medium		Being confined in an intervention hospital decreases the likelihood of being CRP-positive and being wasted by 4 and 9 percentage points. Patients in the intervention are 12 % and 9 % more likely to have health improvement for not wasted and CRP-negative respectively.
8	Sepehri et al. (2011). Country: Vietnam. Scheme: CBHI	Fixed and random effect. Data: Household survey. N=6,037	1	Low		In fixed effect model, CHI and VHI did not have any impact on OOP, but HIP have 16% reduction effects
9	Sosa-Rubi, Salinas-Rodriguez, and Galarraga. (2011). Country: Mexico. Scheme: SHI	DID and IV. Data: Household. N=?	2	Low		At the local level (regional clusters) we did not find an effect of the SP. At the household level, we found a protective effect of SP on CHE and the OOP health payments in outpatient and hospitalization in rural areas; and a significant effect on the reduction of OOP payments in outpatient health services in urban zones.
10	Blanchet et al. (2012). Country: Ghana. Scheme: SHI	PSM. Data: Household survey. N=2543	1	Low	Keeping all other factors constant, NHIS-enrolled women are 40 % more likely to have attended a clinic over the past year, and they have about 57 % more prescriptions. Most remarkably, NHIS enrolled women appear nearly twice as likely (83 per cent more likely) to have stayed overnight at a hospital than non-enrolled women	
11	Chen and Jin (2012). Country: China. Scheme: SHI	DID-PSM. Data: Census. N=3977 - 950,681	3	Low		The NCMS has no obvious effect in reducing the incidence of child or maternal mortality at the village level. the NCMS has no significant effect on school enrolment once we control for the endogenous introduction and take-up of the NCMS

12	Dhillon et al. (2012). Country: Rwanda. Scheme: CBHI	FE with IV (Arellano-Bond approach). Data: Household survey. N=84-950	1	Low	The removal of financial barriers had the single greatest impact on monthly utilisation rates. Its coefficient estimate of 0.6 indicates that the effect of the event of removing financial barriers resulted in a near 100% increase in utilisation from the rate of 0.65 visits per capita per year before the intervention	
13	Fan et al. (2012) Country: India Scheme: SHI	DID, Quintile Regression, and matching method. Data: Household Survey. N=11,881	3	Low		Households in Phase I districts experienced significantly reduced per capita per month inpatient health expenditure by Rs. 12, but not outpatient spending. The first 2 months of implementation of Phase II did not significantly reduce per capita inpatient spending (with effects in the expected direction), although Phase II significantly reduced per capita outpatient drug spending.
14	Lu et al. (2012). Country: Rwanda. Scheme: CBHI	PSM; 2SRI; IV. Data: Household survey. N=1,000 - 6,334	2	Low	Mutuelles enrollees were more likely to use medical services than those without any insurance after controlling for other factors. The odds of using medical care increased by 2 for Mutuelles enrollees. among under-five children that reported diarrhoea, fever, or ARI in the two weeks prior to the survey, Mutuelles enrollees were more likely to use medical care. among women who delivered children in the survey years, Mutuelles enrollees were more likely to use skilled birth attendance.	Mutuelles households were less likely to incur catastrophic health spending.
15	Lu, Liu, and Shen (2012). Country: China. Scheme: SHI	2PM and hurdle model with PSM and IV. Data: Household survey. N=1170 - 2740	2	Low	We have found that the CMS pilot programs have had a significant and positive effect on the probability of seeking medical care (the estimate 1.569) and the number of visits (The marginal effect: 1.20).	The CMS programs did not seem to have had a significant impact on households' out-of-pocket health expenditure and on reducing catastrophic spending

<b>16</b>	Nguyen (2012). Country: Vietnam. Scheme: CBHI	PSM combined with DID; Compared with IV and Fixed effect separately. Data: Household survey. N=6780	3	Low	The voluntary health insurance helps the insured people increase the annual outpatient and inpatient visits by around 45% and 70%, respectively.	The effect of voluntary health insurance on out-of-pocket expenses on health care services is not statistically significant
<b>17</b>	Parmar et al. (2012). Country: Burkina Faso. Scheme: CBHI	FE and IV. Data: Household survey. N=890	2	Low		With OLS, insurance had no significant impact on per capita household assets. In the 2SLS, insurance had a positive effect on per capita household assets (24.6 percent). By FE, insurance increased per capita household assets by 1 percent at 10 percent significant level
<b>18</b>	Robyn et al. (2012). Country: Burkina Faso. Scheme: CBHI	FE. Data: Household survey. N=2820	3	Medium	Odds ratios of 1.33 and 1.23 suggested that individuals residing in areas with insurance scheme were marginally more likely to seek treatment in general, and also to seek facility-based professional care but it is not statistically significant	
<b>19</b>	Robyn et al. (2012). Country: Burkina Faso. Scheme: CBHI	Multinomial Logit and PSM. Data: Household survey. N=1240	1	Low	while enrolment may lead to improved access to facility care within the formal health system, the insured population continues to actively seek drugs from the informal sector, resulting in a continued high prevalence of self-medication within the household.	
<b>20</b>	Wirtz et al. (2012). Country: Mexico. Scheme: SHI	Heckman selection model and PSM&IV. Data: Household survey. N=28,260	2	Low		Being affiliated with SP reduced the probability of incurring medicine expenditure by 9.7% and the annual amount spent for medicine by US\$24.51 but showed no significant effect on the percentage of medicines expenditure on the AE in comparison to households without health insurance.

21	Yilma et al. (2015). Country: Ethiopia. Scheme: CBHI	FE and PSM. Data: Household survey. N=9455	1	Low	We find a negative impact on the probability of having outstanding loans ranging between 4% and 5%, depending on methods and control groups, which translates to about 13% of baseline values. There are also negative coefficients for the amount of outstanding loans although these are imprecise. Estimates for all types of livestock are not statistically significant.
22	Aji et al. (2013). Country: Indonesia. Scheme: SHI	IV and FE. Data: Household survey. N=6335	2	Low	Askeskin decreased out-of-pocket expenditures by 34% and Askes by 55% compared with non-Askeskin and non-Askes, respectively
23	Avilla-Burgos et al. (2013). Country: Mexico. Scheme: SHI	PSM. Data: Household survey. N=12,250	1	Low	SP reduces the likelihood of HE in 3.6 and 7.1% in households with patients diagnosed with DM and/or hypertension, respectively
24	Camacho and Conover (2013). Country: Colombia. Scheme: SHI	RD. Data: Household survey. N=40,931	3	Low	The Subsidized Regime had a significant and positive effect on health, reducing the incidence of low birth weight between 1.7 and 3.8 percentage points. We find that the direction of the impact on very low birth weight, an indicator for the baby being preterm, and for 5-minute Apgar score show an improvement in newborn health, but these results are not always significant
25	Cheung and Padieu (2013). Country: China. Scheme: SHI	IV. Data: Household survey. N=933	2	Low	A significant and negative impact of insurance on participant's saving in third quantiles. No significant impact on the poorest nor the richest. No significant effect on health expenditure regardless of its income quantiles
26	Fink et al. (2013). Country: Burkina Faso. Scheme: CBHI	IV. Data: Randomised study. N=12,118	3	Medium	The average person would save about US\$ 3.8 per year. the insurance rollout was associated with about a 30% reduction in the likelihood of catastrophic expenditure in targeted areas.  The introduction of the insurance scheme did not have any effect on health outcomes for children and young adults, but appears to have increased mortality among individuals aged 65 and older.

27	Hassan et al. (2013). Country: Colombia. Scheme: SHI	Poisson and probit with two-stage nonlinear method of moments. Data: Household survey. N=12,975	1	Low	Individuals who are involved in the program visit a doctor 21% less frequently for preventive health care purposes than individuals who are not in this program. there is a positive effect, which means that individuals enrolled in this program have a higher probability of hospitalization.	
28	Jing et al. (2013). Country: China. Scheme: SHI	DID. Data: Household survey. N=1681	1	Low		Controlling for household demographic characteristics, the coefficient of the interaction term was negative but not statistically significant, suggesting that the reimbursement policies for chronic disease in the NCMS programs were not significantly effective in reducing household CHE
29	Miller et al. (2013). Country: Colombia. Scheme: SHI	Fuzzy RD and IV. Data: Household survey. N=4219 and 3334	3	Low	SR enrolment is associated with a 29-percentage point increase in the probability of a preventive physician visit in the past year, a 13-percentage point increase in reported physician visits because of health problems within the past 30 days, and a 1.50 more growth-monitoring and well-care visits in the past year compared to uninsured children	SR enrolment lowers mean inpatient spending by about 60,000 pesos ( $\alpha=0.10$ ) or 30 % reduction. There is no statistically significant association for outpatient care.  SR enrolment is associated with 1.4 fewer child days absent from usual activities due to illness in the past month ( $\alpha=0.05$ ). Enrolment is also associated with an 18-percentage point reduction in the self-reported incidence of cough, fever, or diarrhoea among children in the preceding two weeks (but it is not statistically significant at conventional levels
30	Nguyen and Wang (2013). Country: Vietnam. Scheme: SHI	DID. Data: Household Survey. N=628 - 1209	2	Low	Overall pattern of increased use of secondary hospitals and decreased use of tertiary hospitals. the use of secondary hospitals increased significantly for both 0-3 and 4-5 years age groups by 0.02 and 0.03 admissions per year, respectively. Number of sick days among the age group 4-5years reduced by 0.81 as a result of FCCU6. Compared with the baseline value of 3.06, this represents 26% reduction.	The probability of having large OOP in this group went down by 1.7 percentage point, which represents nearly 60% of the baseline value (0.027).
31	Sparrow et al. (2013). Country: Indonesia. Scheme: SHI	DID and PSM. Data: Household survey. N=34,525	2	Low	The difference results suggest that Askeskin increased outpatient utilization by 0.062 visits per person per month (vppm), while kernel matching yields an impact of 0.079 vppm.	Askeskin coverage seems to increase OOP payments and budget shares, in particular in urban areas, although the propensity score matching results show larger standard errors. Evidence of increased incidence of catastrophic spending at a 15 percent threshold, but not significant with PSM

32	Zoidze et al. (2013). Country: Georgia. Scheme: SHI	DID. Data: household survey. N=?	1	Low	Individuals with acute sicknesses in the preceding 30 days are more likely to report using health services and report a substantial increase in utilisation from 2007, with 66% consulting a health care provider in 2010 compared with 57% in 2007. However, the individuals with chronic illnesses utilised less services resulting in zero net effect for an overall use of services	Less OOP expenditure for inpatient services (-227 Gel per episode) and total monthly health care payments (-27 Gel), but a dramatic increase in the shares of the general population facing the catastrophic health expenditure from 11.7% in 2007 to 24.8% in 2010
33	Abrokwah et al. (2014). Country: Ghana. Scheme: SHI	OLS with proxy and 2PM. Data: Household survey. N=1012	1	Low	Having insurance increases the number of prenatal care visits by 24% relative to being uninsured.	The predicted total out-of-pocket spending on prenatal care for an insured pregnant woman is about C  3,600 (\$0.40) for her first prenatal care visit, while the predicted total spending for an uninsured pregnant woman stands at about C  21,600 (\$2.40) for her first visit
34	Bai and Wu (2014). Country: China. Scheme: SHI	DID and matching method. Data: Household survey. N=17,715	3	Low		Insurance coverage on average stimulated nonmedical consumption by 5.5% for the insured (p<0.1). the insurance effect does not appear to be driven by the crowd-in story because the NCMS effect is substantial even for households that do not incur medical expenditures. the insurance effect increases with the generosity of insurance coverage at the county hospitals.
35	Bernal et al., (2014). Country: Peru. Scheme: SHI	Fuzzy RD. Data: Household survey. N=4161	3	Low	Being covered by health insurance increases the probability of visiting a doctor in the four weeks prior to the interview by 51.5 percentage points. The probability of obtaining medicines in the same four weeks increases by 52.7 percentage points. The probability of being vaccinated in the three months prior to the interview increases by 28.9 percentage points, and women at fertile age are 65.0 percentage points more likely to control their pregnancy in the previous twelve months	We find that health insurance coverage increases the probability that individual health expenditures exceed 5 and 10 percent of the per capita household income by 40.6 and 29.1 respectively. Overall, it is remarkable that we never find a negative effect on either expected health expenditures or measures of variability or risk of high expenditures.
36	Chen et al. (2014). Country: China. Scheme: SHI	Bivariate probit. Data: Household survey. N=43,381	2	Low	Increased the likelihood of hospitalisation in the past year (1.8% probit); increased the likelihood of refused inpatient treatment in the past year; increased outpatient health services utilisation (1.7%).	

37	Guindon (2014). Country: Vietnam. Scheme: SHI	DID, FE, and DID-PSM; 2PM. Data: Household survey. N=6775	2	Low	HCFP coverage is not found to impact the utilization of outpatient services with the exception that HCFP coverage appears to increase the probability of having had at least one outpatient visit. Using PSM the magnitude is smaller for outpatient, but bigger for inpatient admissions.	
38	Hendriks et al. (2014). Country: Nigeria. Scheme: CBHI	DID. Data: Household survey. N=413	1	Low		Systolic blood pressure decreased by 10.41 mm Hg (P < .001) from 2009 to 2011 in the program area. This reduction was 5.24 mm Hg (P = .02) greater compared with the control area. Diastolic blood pressure decreased by 4.27 mm Hg (P < .001) in the program area, 2.16mmHg (P = .04) greater reduction compared with the reduction in the control area, where diastolic blood pressure decreased by 2.11 mm Hg. Self-reported general use of health care resources increased in the program area and decreased in the control area and it's significantly different between areas when corrected for confounders (OR, 2.47; P = .006)
39	Hou et al. (2014). Country: China. Scheme: SHI	FE with 2PM & Generalized Linear Model. Data: Household survey. N=1,478 - 28,824	2	Low	A 1-percentage point increase in NCMS generosity raises the probability of using inpatient care by 0.004, which corresponds to an increase of about 7.5% compared with the overall sample probability (0.053). the SPA (Social pooling account) system for outpatient care proves to be more effective in improving access than the system of household MSAs (medical saving account)	No effects are found of NCMS on spending in the full sample, but conditional upon use, NCMS reduces the share of OOP spending for an outpatient visit. More worrisome is that we find higher NCMS cover to raise total spending per hospitalization and to increase the OOP spending per inpatient stay (among the users)
40	Liu and Zhao (2014). Country: China. Scheme: SHI	IV. Data: Household survey. N=628	2	low	Participation in the URBMI has significantly increased the probability of individuals' use of formal medical care, by 10-15 percentage points, increased likelihood of outpatient by 7-13 %, increased the number of inpatient days by 0.35-0.5 days but not the probability.	Joining URBMI resulted in an increase in out-of-pocket health expenditures of about 11-172 RMB, although the coefficients are insignificant
41	Liu, Wu, and Liu (2014). Country: China. Scheme: SHI	Structural equation modelling. Data: survey. N-1645	1	low		Taking the direct and indirect effects together, patients enrolled in the scheme had to pay 351 yuan more out-of-pocket than the uninsured, although this total effect was statistically insignificant (for NCMS)



42	Nguyen (2014). Country: Vietnam. Scheme: SHI	PSM. Data: Household survey. N=15,550	1	Low	On average, a person with compulsory insurance pays 0.47 visits to health care facilities more than their uninsured counterpart. there is no moral hazard or adverse selection in using inpatient services.	
43	Pfutze (2014). Country: Mexico. Scheme: SHI	Weighted Exogenous Sampling Max Likelihood. Data: Household survey. N=836,809	2	Low		The risk of a child dying in the first month of life is reduced by close to 5 out of 1,000 (or 0.5%) for the population at large and by around 7 out of 1,000 (0.7%) for the program's target population.
44	Sheth. (2014) Country: India. Scheme: CBHI	DID. Data: Randomised Study N=1311	3	Low	Contrary to the majority of studies evaluating CBHI, the author found that the insurance contract does not increase health care consumption. Instead, the author found limited suggestive evidence of the insurance possibly reducing the consumption and expenditure of health care.	Limited suggestive evidence of the insurance possibly reducing the consumption and expenditure of health care.
45	Sood et al. (2014). Country: India. Scheme: SHI	RD and DID. Data: Household survey. N=986 - 22,796	2	low	Although this result was not significant at the 95% level, the point estimate was large and approached significance, which could suggest of a positive effect on utilization	The scheme was associated with a 34% reduction in out-of-pocket health expenditure for admission to hospital for covered conditions  The mortality rate from conditions covered by the scheme was 0.32% in eligible households compared with 0.90% in ineligible households (difference of 0.58 percentage points, 95% confidence interval 0.40 to 0.75; P<0.001; 64% risk reduction).
46	Yuan et al. (2014). Country: China. Scheme: SHI	DID. Data: Administrative data. N=720	2	Low		The DID regression analysis showed no impact of benefit design on patients' out-of-pocket expenses, which indicates that the expansion of public health insurance coverage did not have any effect on relieving financial burden of disease for AMI patients
47	Alkenrack and Lindelow (2015). Country: Lao. Scheme: CBHI	PSM. Data: Household survey. N=3000	2	Low	CBHI members were almost twice as likely as non-members to have had an inpatient visit in a 1-year period. Regarding source of care, the matched estimates show that CBHI members were significantly more likely than non-members to visit both district and provincial hospitals, for both inpatient and outpatient care.	No significant difference in expenditures between the insured and uninsured. This lack of difference in spending indicates positive financial protection in that the insured are using more services, paying less at the point of service, but spending approximately the same amount overall as the uninsured.

48	Atella, Brugiavini, and Pace. (2015). Country: China. Scheme: SHI	Finite Mixture Model (Bayesian). Data: Household survey. N=3166	2	Low		In particular, we find that out-of-pocket expenses decrease only for high income individuals with good health status and the saving rate increases only for low income individuals with good health status.
49	Brugiavini and Pace (2015). Country: Ghana. Scheme: NHI	IV. Data: Household survey. N=9,396	2	Low	The NHIS enrolment positively affects the probability of formal antenatal check-ups before delivery, the probability of delivery in an institution and the probability of being assisted during delivery by a trained person.	On the contrary, we find that, once the issue of self-selection is considered, the NHIS enrolment does not have a significant effect on out-of-pocket expenditure at the extensive margin
50	Cheng et al. (2015). Country: China. Scheme: SHI	PSM and DID. Data: Household survey. N=6598	3	Low	We also find that the elderly participants are more likely to get adequate medical services when sick, which provides a good explanation for the beneficial health effects of the NCMS. Furthermore, it is found that low-income seniors benefit more from NCMS participation in terms of health outcomes and perceived access to health care	We find no evidence that the NCMS has reduced the elderly enrollees' out-of-pocket spending. We find no significant effect of the NCMS on 3-year mortality for the previously uninsured elderly in NCMS-exposed counties, although there is moderate evidence that NCMS is associated with reduced mortality for the elderly enrollees.
51	Fenny et al. (2015). Country: Ghana. Scheme: SHI	Multinomial Logit. Data: household survey. N=11,089	1	Low	those insured are 6 times more likely to choose regional/district hospitals and health centres/clinics and 11 times more likely to choose private hospitals/clinics over informal care when compared to those uninsured and this is significant at 1%	
52	Ghislandi, Manachotphong, and Perego. (2015). Country: Thailand. Scheme: SHI	Triple DID with PS; Double Robust. Data: Household data. N=15,022	2	Low	UHC increases individuals' likelihood of having an annual check-up, especially among women. Regarding health care consumption, we observe that UHC increases hospital admissions by over 2% and increases outpatient visits by 13%.	
53	Gotsadze et al. (2015). Country: Georgia. Scheme: SHI	DID. Data: Household survey. N=11,663	1	Low	MIP-enrolled individuals were marginally (by 2%) more likely to utilize any formal health care services (P<0.1).	The largest reduction was observed for inpatient spending—at 227 Gel per case. Although most financial impact indicators for the overall sample revealed marginal statistical significance (P<0.1)

54	Grogger et al. (2015). Country: Mexico. Scheme: SHI	Logistic regression. Data: Randomised study N=83,000	3	Medium		In rural areas, remote from health-care facilities, or proximate only to facilities with limited staffing, the programme has not reduced catastrophic out-of-pocket health expenditures. In rural areas proximate to larger facilities, in contrast, the programme has provided considerable financial protection. Also in urban areas, SP has substantially reduced catastrophic out-of-pocket health spending among beneficiaries
55	Jung and Streeter (2015). Country: China. Scheme: SHI	SSM + 2PM and IV. Data: Household survey. N=50,591	2	Low		Our results from a selection model with instrumental variables suggest that having health insurance reduces the expected OOP health expenditure of an individual by 29.42% unconditionally. Meanwhile, conditional on being subjected to positive health expenditure, health insurance helps reduce OOP spending by 44.38%.
56	Limwattananon et al. (2015). Country: Thailand. Scheme: SHI	DID and GLM; censored quintile regression. Data: Household survey. N=26,557	2	Low	In terms of utilization, we get a highly significant DID estimate of one percentage point, which is 16% of the baseline admission probability of the treatment group. It is almost three percentage points for the elderly, while the point estimate is only half a point and not significant for children	The reform reduced OOP spending by an average of almost 19 Baht (~\$0.47) per person per month and by 28% relative to what spending would have been in the absence of the policy. The reform is estimated to have reduced the probability of spending at least 10% of the household budget on health care by a significant 1.6 percentage points (38%).
57	Makhloufi et al. (2015). Country: Tunisia. Scheme: SHI	PSM. Data: Household survey. N=6538	1	Low	Given illness amongst the MHI enrolees, the increases in outpatient and inpatient care range from 18.8 to 21.4 %point and from 25.8 to 38 % point, respectively, compared with a significant increase in outpatient of about 15 % point in the rural areas and no significant increase in inpatient care.	The excluded households appeared to spend almost twice as much on healthcare as the MAS beneficiaries (25.1 for the excluded vs. 13.85 for MAS beneficiaries), while their average healthcare expenditure appeared to be slightly higher than that of the MHI enrolees (25.1 for the excluded vs. 23.1 for the MHI). this indicates that although MHI seems to have an effect on the use of healthcare, its effect on healthcare expenditures appears to be rather modest, as it does not significantly reduce healthcare expenditure of insured beneficiaries compared with excluded individuals and MAS beneficiaries.
58	Palmer et al. (2015). Country: Vietnam. Scheme: NHI	RD. Data: Household survey. N=18,517	3	Low	Insurance increases the probability of an inpatient visit by 6.8% and an outpatient visit by 21.7%; the average number of inpatient and outpatient visits increases by 1.13 and 0.75, respectively.	The impact of insurance on expenditures is positive for both service types. However, the impact is not statistically significant.

59	Pfütze (2014). Country: Mexico. Scheme: SHI	Weighted Exogenous Sampling Max Likelihood. Data: Household survey. N=27,455	1	Low			For the target population, a one percentage point increase in eligibility is found to decrease miscarriages by .04 percentage point at the average
60	Yang and Wu (2015). Country: China. Scheme: SHI	2PM; PSM and DID; Heckman Selection model. Data: Household survey. N=4084	2	Low			The PSM with DID estimates for outpatient costs. The results show a trend of increase in pre-reimbursement outpatient costs (gross billed) between the treatment group compared with the control group (P<0.1). The results also show that there is no significant difference in post reimbursement outpatient costs (OOP payments) for the control group and treatment group after NCMS reimbursement
61	Yilma et al. (2012). Country: Ghana Scheme: SHI	PSM and FE. Data: Household survey. N=761	3	Low	Like the non-parametric estimation, the fixed effects model indicates that in 100 insured households, around 20 people do not sleep under STNs due to insurance uptake. Health insurance apparently increases the benefit of curative care relative to preventive care, and most strongly so if the level of effort, cost and discomfort involved in prevention is higher (the case of STNs).		
62	Aryeetey et al. (2016). Country: Ghana. Scheme: NHI	IV-FE. Data: Household survey. N=3128	2	Low			Our results revealed that enrolment into health insurance reduces household OOPE by 86 %. The effect of health insurance is protective i.e. insured households were 3 % less likely to incur CE and 7.5 % less likely to fall into poverty.
63	Levine, Polimeni, and Ramage (2016). Country: Cambodia. Scheme: CBHI	IV. Data: Randomised study. N=5,000	3	Medium	Insured households were 15.8 percentage points more likely to use a health centre for first treatment (P < 0.001) and 10.7 and 8.0 percentage points less likely to visit a private doctor or drug seller for first treatment compared to the control group. No statistically significant impact of SKY on first treatment at a public hospital	No impact on overall wealth; households that purchased SKY due to the steep discount were 10.8 percentage points less likely than the control to have at least one of these adverse economic outcomes	There is no significant difference between treated and control households for this index of health measures

64	Liao, Gilmour, and Shibuya (2015). Country: China. Scheme: SHI	PSM. Data: Household Survey. N=9971	1	Low	Among diagnosed hypertensives, health insurance increased the probability that they would receive treatment by 28.7% (95% CI: 10.6–46.7%, p-value 0.001) compared to propensity matched individuals who were not covered by health insurance	
65	Nguyen (2016). Country: Vietnam. Scheme: NHI	FE. Data: Household survey. N=5013	2	Low	In 2010-2012, The student health insurance and free health insurance programs increased the number of health care visits of children by approximately 13.6 and 66.1 %, respectively.	Having free health insurance reduced the out-of-pocket health expenditures per visit by around 15.8 in the period 2006–2008 and 63.4 % in the period 2010–2012. Student insurance has no effect
66	Peng and Conley (2015). Country: China. Scheme: SHI	IV and DID. Data: Household survey. N=8309	2	Low		NCMS does significantly decrease children's malnutrition probability by 6.5 % points. The OLS estimations show that the average 3-day food consumption of women at child-bearing age increases by 261 calories after enrolling in the NCMS.
67	Raza et al. (2016). Country: India. Scheme: CBHI	IV. Data: Randomised study. N=21,372	3	Medium	Our analysis reveals that the schemes had no impact on access to outpatient or inpatient care.	We do not find any impact on healthcare expenditure.
68	Rivera-Hernandez et al. (2016) Country: Mexico. Scheme: SHI	FE-IV. Data: Household survey. N=5307	2	Low	The effect of SP on use of insulin and/or oral agents was marginally significant (p = .051), showing a tendency that SP beneficiaries with diabetes were more likely to use pharmacological treatment. No significant difference was found for antihypertensive medication for SP enrollees as opposed to the uninsured.	

**Table A-5 Rosenbaum bounds analysis for the JKN Contributory group (Chapter 7)**

Gamma	Any Outpatient		# visit (total)		# visit (Public)		# visit (Private)		Any Inpatient		# visit (total)		# visit (Public)		# visit (Private)	
	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-
1	0.00	0.00	0.01	0.01	0.03	0.03	0.08	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.1	0.00	0.00	0.13	0.00	0.16	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.2	0.00	0.00	0.50	0.00	0.45	0.00	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.3	0.01	0.00	0.86	0.00	0.75	0.00	0.97	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
1.4	0.06	0.00	0.98	0.00	0.92	0.00	1.00	0.00	0.00	0.00	0.10	0.00	0.01	0.00	0.01	0.00
1.5	0.22	0.00	1.00	0.00	0.98	0.00	1.00	0.00	0.00	0.00	0.26	0.00	0.03	0.00	0.03	0.00
1.6	0.48	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.47	0.00	0.06	0.00	0.06	0.00
1.7	0.31	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.68	0.00	0.12	0.00	0.12	0.00
1.8	0.13	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.84	0.00	0.21	0.00	0.21	0.00
1.9	0.04	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.93	0.00	0.33	0.00	0.33	0.00
2	0.01	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.97	0.00	0.45	0.00	0.45	0.00

**Table A-6 Rosenbaum bounds analysis for the JKN Subsidised group (Chapter 7)**

Gamma	Any Outpatient		# visit (total)		# visit (Public)		# visit (Private)		Any Inpatient		# visit (total)		# visit (Public)		# visit (Private)	
	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-	P+	P-
1	0.11	0.11	0.99	0.99	0.42	0.42	0.00	0.00	0.00	0.00	0.24	0.24	0.18	0.18	0.75	0.75
1.1	0.41	0.00	1.00	0.65	0.92	0.03	0.00	0.00	0.00	0.00	0.71	0.02	0.53	0.03	0.93	0.44
1.2	0.05	0.00	1.00	0.06	1.00	0.00	0.00	0.23	0.00	0.00	0.96	0.00	0.84	0.00	0.99	0.19
1.3	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.82	0.02	0.00	1.00	0.00	0.97	0.00	1.00	0.06
1.4	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.99	0.07	0.00	1.00	0.00	1.00	0.00	1.00	0.01
1.5	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.17	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1.6	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.34	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1.7	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.52	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1.8	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.34	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1.9	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.20	0.00	1.00	0.00	1.00	0.00	1.00	0.00
2	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.10	0.00	1.00	0.00	1.00	0.00	1.00	0.00

**Table A-7 Logit regression table for JKN participation among the contributory group**

Variables	Coefficient	Standard error	P - value	Upper 95% CI	Lower 95% CI
Sampling weight	0.23	0.12	0.06	-0.01	0.47
Age	-0.01	0.02	0.68	-0.04	0.03
Gender (1 = male)	-0.21	0.08	0.01	-0.36	-0.07
Single	0.48	0.22	0.03	0.05	0.91
Married	0.59	0.19	0.00	0.22	0.97
Urban	0.79	0.10	0.00	0.60	0.98
Primary education	0.04	0.22	0.87	-0.39	0.46
Secondary education	0.63	0.22	0.01	0.19	1.08
College education	1.17	0.28	0.00	0.63	1.72
Higher education	1.10	0.26	0.00	0.59	1.62
Assets index	0.13	0.03	0.00	0.07	0.19
Number of acute conditions	0.09	0.05	0.05	0.00	0.18
Number of chronic condition	0.18	0.18	0.31	-0.17	0.54
Any disability	0.67	0.32	0.04	0.04	1.30
Density of outpatient care facilities	0.37	0.18	0.04	0.01	0.72
Density of inpatient care facilities	-1.80	0.82	0.03	-3.41	-0.19
Assets index - squared	0.04	0.01	0.00	0.01	0.06
Age- squared	0.00	0.00	0.94	0.00	0.00
Density outpatient - squared	0.00	0.01	0.37	-0.02	0.01
Density inpatient - squared	0.17	0.09	0.08	-0.02	0.35
Acute conditions - squared	-0.01	0.01	0.08	-0.02	0.00
Chronic conditions - squared	-0.04	0.07	0.55	-0.17	0.09
Constant	-3.70	0.48	0.00	-4.64	-2.77



**Table A-8 Logit regression table for JKN participation among the subsidised group**

Variables	Coefficient	Standard error	P - value	Upper 95% CI	Lower 95% CI
Sampling weight	0.11	0.09	0.19	-0.06	0.28
Age	0.00	0.01	1.00	-0.02	0.02
Gender (1 = male)	-0.09	0.05	0.10	-0.20	0.02
Single	-0.24	0.13	0.06	-0.50	0.01
Married	0.20	0.10	0.04	0.01	0.39
Urban	0.53	0.06	0.00	0.40	0.65
Primary education	0.15	0.10	0.12	-0.04	0.34
Secondary education	-0.05	0.11	0.67	-0.26	0.17
College education	-0.77	0.29	0.01	-1.33	-0.21
Higher education	-0.78	0.25	0.00	-1.26	-0.29
Assets index	-0.44	0.03	0.00	-0.49	-0.39
Number of acute conditions	0.05	0.03	0.12	-0.01	0.10
Number of chronic condition	0.14	0.13	0.30	-0.12	0.40
Any disability	0.14	0.26	0.59	-0.37	0.66
Density of outpatient care facilities	-0.14	0.27	0.61	-0.68	0.40
Density of inpatient care facilities	2.78	2.00	0.17	-1.15	6.71
Recipients of unconditional cash transfer	0.76	0.06	0.00	0.65	0.87
Assets index - squared	-0.07	0.01	0.00	-0.08	-0.05
Age- squared	0.00	0.00	0.22	0.00	0.00
Density outpatient - squared	0.02	0.02	0.18	-0.01	0.05
Density inpatient - squared	-1.52	0.81	0.06	-3.11	0.07
Acute conditions - squared	0.00	0.00	0.25	-0.01	0.00
Chronic conditions - squared	-0.08	0.06	0.19	-0.19	0.04
Constant	-1.76	0.31	0.00	-2.36	-1.15

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