Essays in Labour Market Economics

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Abstract

This thesis conducts three empirical investigations in the field of labour market economics. First, an investigation into the relationship between mental-health levels with labour market status and labour market transitions is made using longitudinal survey data spanning 25 years. The results show that unemployment and long-term sickness are associated with lower levels of mental-health compared to individuals who are employed. A transition from employment into unemployment or long-term sickness results in lower levels of mental-health. The reverse transitions, while finding positive effects on mental-health, have asymmetrically lower effect sizes. The next two chapters undertake an evaluation of the In-Work Progression (IWP) Randomised Controlled Trial in the UK. The thesis investigates the impacts of the IWP Active Labour Market Programme (ALMP) over the income distribution of the trial participants to identify how effects varied across income quantiles. The results show that claimants at the higher end of the income distribution achieved higher levels of income progression compared to those at the lower end of the income distribution. The thesis also conducts an examination of how the impact of the trial evolves over time for the participants. Overall, the results show that since entry into the trial, participants have higher income progression over time. The ALMP evaluation results are subsequently analysed between cohorts of men and women, age groups, regions, and Live-service vs Full-service claimants and the estimated effects show considerable heterogeneity.

Keywords:

Labour Economics, British Household Panel Survey, Understanding Society, Active Labour Market Policy Evaluation, In-Work Progression Randomised Controlled Trial, Universal Credit, Department for Work & Pensions.

Declaration

I certify that the thesis I have submitted for examination for the award of a Ph.D. degree by the University of Sheffield is solely my own work, other than where I have clearly indicated otherwise.

I certify that this thesis consists of approximately 50,000 words.

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Dedication

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11 December 1957 to 8 October 2020

General Secretary - National Fishworkers Forum (NFF)

President - Kerala Independent Fishworkers Federation (KSMTF)

Rest in Peace my Friend. Your legacy is as abundant as the Ocean.

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1 Introduction

Labour markets are an integral part of a modern economy. Previous research has contributed to a wide range of knowledge on labour market economics. Over time, the field has evolved from traditional theory based research such as Snower (1995) and into more methodologically rigorous empirical investigations that are elaborated in Blundell and Dias (2009). This is a trend that is expected to continue as more economic data is made available. Recent advances into labour market research such as Bredgaard (2015) has also taken the approach of testing theory with empirical data to be able to arrive at causal inferences. The methodological limitations to such empirical research are also well documented in Smith (2000).

A primary function of labour market research has mostly been to suggest measures to boost employment levels in the economy and maintain the productivity of the labour force. This has been aided by the increasing role of the government in labour markets through the regulatory framework. In the past few decades, Active Labour Market Programmes (ALMPs) have become mainstream and a multitude of government programmes to help support labour market participants have been undertaken. Card et al. (2017) and Vooren et al. (2019) provide an excellent overview of the various ALMPs implemented and their estimated impacts. Specifically, in the United Kingdom (UK) there has been extensive reform of the social security and unemployment benefit systems in recent years.

Further, labour market research has also extended into studying linkages with related fields such as physical health, mental-health and individual wellbeing. In this context, the present research aims to make a twofold contribution to the existing literature. Firstly, we investigate labour market transitions and their relationship with mental-health for individuals. Secondly, we undertake an evaluation of the impacts of a nationwide ALMP in the UK.

1.1 Motivation and Objectives

The first empirical chapter of this thesis builds upon previous research by Schmitz (2011), Kassenboehmer and Haisken-DeNew (2009) and Flint et al. (2013) that have investigated the relationship between unemployment and mental-health. While Arrow (1996), Butterworth et al. (2012), García-Gómez et al. (2010) and Kesavayuth and Zikos (2018) have also contributed to establishing the importance of the reverse effect of mental-health on labour market outcomes. The evidence shows a two directional causal relationship which is often difficult to accurately measure as noted by Kuhn et al. (2009), Frijters et al. (2005) and Gallo et al. (2000). Further, Paul and Moser (2009), Murphy and Athanasou (1999) and Modini et al. (2016) conduct meta-analyses of studies related to unemployment and mental-health and present evidence from previous research that show a significant relationship between both variables of interest.

Within this context, the thesis conducts an investigation into the relationship between labour market status and labour market transitions with mental-health levels of individuals over a 25 year panel dataset with the aim of exploring the relationship between both variables of interest, over a much longer time-period than usually considered in the existing literature. This is an important question as it improves our understanding of how labour market interactions affect the psychological wellbeing of the labour force.

The investigation of the effects of ALMPs have been an increasing point of focus for economists over the past few decades as more and more public resources are devoted to the implementation of labour market programmes. ALMPs have now become main stream with most developed economies having specific departments entrusted with the task of improving labour market outcomes, often for disadvantaged groups. This is an important task as previous studies such as Uhlendorff (2006), Cappellari (2007), Clark and Kanellopoulos (2013), Cai (2014), Mosthaf (2014) and Fok et al. (2015) have noted that low paid worked are at an increased risk of continuing in low pay for the future as well. Labour market programmes are often focused on improving outcomes for the lowest paid workers and therefore this field of research finds direct policy relevance.

A strong foundation of previous research related to ALMP theory and evaluation already exists. Snower (1995) provides a theoretical framework for evaluation and better understanding of ALMPs. Smith (2000) highlights the key methodological challenges for empirical estimation of the effects of ALMPs. Calmfors (1994) presents a micro-economic framework for analysing the various effects of ALMPs and Bredgaard (2015) argues for a integrated framework that combines experimental methods with programme theory evaluations for proper understanding the results of ALMPs. Further, Blundell and Dias (2009) provides an in-depth review of various evaluation methods for empirical estimation of the effects from ALMPs. Finally, meta-analyses of ALMP evaluations by Card et al. (2017) and Vooren et al. (2019) provide useful summaries of the findings from previous research conducted. This thesis contributes to the existing literature in the field of ALMP evaluation through a direct investigation of the effects of a nationwide ALMP in the UK.

1.2 Thesis Overview

This thesis consists of three research chapters. Chapter 2 investigates the relationship between labour market status and labour market transitions with mental-health levels over a 25 year panel dataset. Chapters 3 and 4 evaluate the effects of an Active Labour Market Programme in the UK: The In-Work Progression Randomised Control Trial was administered by the Department for Work & Pensions during 2015 to 2018. The present research has implications for research on mental-health outcomes stemming from labour market shocks as well as evaluation of ALMPs in the UK and in a worldwide context. The overview for each chapter is provided below.

1.2.1 Overview of Chapter 2

Chapter 2 uses panel data over 25 years from the harmonised British Household Panel Survey and the UK Household Longitudinal Study (commonly referred to as Understanding Society) in the United Kingdom to assess the relationship between mental-health levels associated with contemporaneous status and transitions in the labour market. The main contribution of this chapter to the existing literature is the assessment of the impacts of labour market shocks on mental-health levels over the long period of data spanning 25 years.

The dataset used involves household annual survey data from 1991 to 2017 in a longitudinal setting from across the UK. Self reported psychological well-being as defined by the General Health Questionnaire (GHQ) is the primary dependent variable in the study. The GHQ involves 12 different questions relating to mental-health of the individual that is recorded as an inverse scale from 1 to 4, signifying lower mental-health for higher GHQ scores. The independent variables include employment status that covers the full range of labour market status including Employed, Self-employed, Unemployed, Retired, Maternity Leave, Family Care, Full Time Student, Government Training Scheme, Unpaid Worker and Apprenticeship. Further, labour market status transition variables were generated to identify movements of individuals from one status to another. Finally, a set of suitable control variables were also included that included relevant socio-economic variables.

The research makes use of four Fixed Effects regression models of different specifications. Model 1A and 1B investigate the significance of labour market status on mental-health levels. In Model 2A we investigate the relationship between mental-health and labour market transitions, while Model 2B included labour market status as well as labour market transitions into the specification. We check the robustness of the results by comparing results from the original Fixed Effects models with Ordinary Least Squares (OLS) regressions. Further, gender based sub-samples allow for the estimation of comparable effects between men and women.

The results showed significant negative effects on mental-health levels associated with the unemployed and long-term sick when compared to the employed. The investigation of labour market transitions revealed negative effects for those transitioning from employment to unemployment and into long-term sickness as well as negative effects for those remaining in unemployment and long-term sickness. The evidence indicates that in addition to the direct economic consequences associated with a job loss, there are also important mental-health implications associated with job losses and other labour market transitions. Further, the effect sizes on mental-health levels associated with labour market transitions shows asymmetry. Reverse transitions into employment have positive but smaller effect sizes. The data also indicates the possible existence of adaptation for mental-health impacts associated with labour market interactions.

1.2.2 Overview of Chapter 3

Chapter 3 conducts an investigation of the effects of an Active Labour Market Policy in the United Kingdom. The Department for Work & Pensions (DWP) conducted a Randomised Control Trial to assess the impacts of In-Work Progression on low income Universal Credit claimants. The trial was operational from 2015 to 2018 across the UK and saw the participation of over 31,500 low income benefit claimants.

The main aim of the IWP trial was to offer support to claimants to help them achieve progression in earnings by working more hours or from higher paying jobs. The trial was designed with three treatment arms representing the various levels of support available to the claimants from the Jobcentre through Work Search Reviews (WSR) conducted by work coaches. The 3 treatment arms included, the Minimal support group with one WSR at the time of entry into the trial and another WSR after 8 weeks, the Moderate support group which received a WSR every 8 weeks, and the Frequent support group which had a WSR every 2 weeks. Entry into the trial was triggered when a low income claimant went above a certain threshold of earnings per month. Assignment into one of the three IWP support groups was randomised based on the last three digits of the National Insurance number of each claimant.

A specific untreated group to the IWP trial did not exist and the Minimal support group which received the least form of support serves as the comparison group in the present research. The data used for the research was provided by DWP Administrative Datasets which were also linked with HMRC Real Time Earnings Information that provided 130 weeks of earnings data for all participants. This included 52 weeks prior to the start of the trial and 78 weeks after entry into the trial. The data also contained anonymised information of claimant IWP support group, age, gender, region, Live-Service vs Full Service and date of trial start.

Essentially, the IWP trial was designed with the different levels of support and previous research by the DWP has investigated how effective higher levels of support were for achieving increased earnings outcomes. This chapter investigates further by estimating the treatment effects across select quantiles of the weekly earnings distribution. The essential question of interest is, where along the earnings distribution are higher levels of income progression observed. Further, we check for heterogeneity in treatment effects across sub-samples of male vs female, age cohorts, Live-service vs Full-service and different regions in the UK.

Overall, the analysis revealed positive effects from the IWP trial associated with Moderate and Frequent support relative to the Minimal support group. Trial participants at higher levels of the weekly earnings distribution saw significantly better outcomes compared to those at lower levels of the earnings distribution. Further, women were seen to have much better earnings outcomes under both Moderate and Frequent support groups compared to men. In terms of age, the Moderate support seemed to work well for those aged above 35 years. Notably, while the Frequent support group had positive outcomes associated with the trial participants aged between 18-25 and those aged between 36-45, the effects were negative for those above 55 years of age. Further analysis also revealed that the key driver of the positive income increases from the In-Work Progression ALMP are women above 35 years of age.

1.2.3 Overview of Chapter 4

Chapter 4 delves deeper into the effects of the In-Work Progression RCT by the Department for Work and Pensions in the UK. The primary focus of this chapter is to evaluate the treatment effects over time, after start of the IWP trial. The research methodology incorporates a Difference in Difference model with the same primary dataset as used in the previous chapter.

The dataset provides for 78 weeks (18 months) of claimant earnings data after entry into the trial. This period of 18 months, which is defined as the observation period of interest, is further divided into comparable 3 month time periods using mutually exclusive time dummies. The effects of the IWP trial are estimated for each three month period to check when claimants had higher income progression through participation in the trial.

Subsequently, the differential treatment effects across each three month period is investigated for the Moderate and Frequent support groups relative to the Minimal support group. The research also conducts an investigation into how the results varied for sub-samples of claimants between men vs women and Live-service vs Full-service claimants.

The results showed that differences in weekly wages persist between the Minimal support group with Moderate and Frequent support groups even after 18 months post start of the trial. Notably, we also find significant heterogeneity in the estimated impacts across the Moderate and Frequent support groups, men & women as well as between Live-service & Full-service claimants.

The Moderate support group had better income progression results across all time periods investigated when compared to the Frequent support group. Women had consistently better outcomes from the IWP trial for both Moderate and Frequent support throughout the observation period. Full-service claimants had higher income progression through participation in the Moderate support group while Live-service claimants generally had better outcomes in their weekly earnings under Frequent support, throughout the 18 months investigated. Overall, the analysis revealed that treatment effects steadily increased over the observation period with a peak in the estimated effects around 12-15 months after entry into the trial.

Finally, the research investigates possible calendar effects to check if treatment effects varied over the course of the 3 years of entry into the trial. The results are compared for claimants entering the trial in 2015, 2016 and 2017. The estimated treatment effects of the IWP trial was not significantly different for claimants based on year of entry.

2 Relationship between Labour Market Transitions and Mental-Health

2.1 Introduction

The event of unemployment is widely accepted to be a significant shock for an individual. While the primary impact is usually seen to be on income, it is generally accepted that unemployment also affects an individual's wellbeing through social and psychological mediums. Previous research by Murphy and Athanasou (1999) and Fryer and Fagan (2003) has investigated the health impacts from unemployment and concluded that spells of unemployment has negative impacts for mental health. Notably, research by Clark (2003) and McKee-Ryan et al. (2005) demonstrate that negative mental-health impacts from unemployment includes anxiety, depression, loss of social identity and the perception of social exclusion. The impact on income from unemployment is usually easier to investigate, quantify and mitigate. An investigation of the impact of unemployment on mental wellbeing however faces numerous methodological challenges.

Firstly, the definition of mental-health and how it ought to be measured is subjective and prone to interpretation. Secondly, endogeneity may face the researcher in the form of negative selection, wherein the pool of unemployed individuals may often suffer from lower mental-health. The cause of unemployment needs to be exogenous in-order to be able to arrive at a reliable conclusion regarding causality of the relationship. Thirdly, the issue of reverse causality cannot be ignored as deteriorating mental-health may itself be the cause of the unemployment.

A multitude of studies including Schmitz (2011), Kassenboehmer and Haisken-DeNew (2009) and Flint et al. (2013) have investigated the link between unemployment and mental-health and have been able to establish that the unemployed tend to have poorer levels of mental-health. Further, previous research by Warr and Jackson (1985), Kessler et al. (1989), Lahelma (1989), Isaksson (1990) also show that re-employment can moderate the negative health effects from unemployment.

The reverse possibility where mental-health impacts on the probability and duration of unemployment are also shown to be significant in Arrow (1996), Butterworth et al. (2012), García-Gómez et al. (2010), Kesavayuth and Zikos (2018). Further, labour market studies have often focussed solely on the dual status of being employed and unemployed and failed to capture the multi-dimensional aspects of the various labour market status that exist in reality. Central to this line of research is the need to extend labour market status to include the various other possibilities and to study the implications for mental well-being associated with these other status. Additionally, the nature of work such as job quality, job security and job satisfaction are also known to affect an individual's well-being as shown by Broom et al. (2006) and Grun et al. (2010). Therefore, the existing literature shows evidence implying that causality between labour market transitions and mental-health may be bi-directional and contextual.

In this context, this research uses panel data from the British Household Panel Survey (BHPS) and the Understanding Society (US) household survey in the United Kingdom to undertake an investigation into the various labour market status and transitions, and their associated impacts on mental health. Investigating the impact of labour market transitions on mental-health is also expected to be of relevance, since findings in existing literature show that the event of losing a job or the transition between two labour market states contributes to a change in wellbeing. The nature of labour market transitions also imply the possibility that reverse transitions could have asymmetry in their impacts on mental-health.

The terms "mental-health" and "wellbeing" represent self-reported indicators of an individual's overall state of mind or happiness and is derived from the survey data used. They are used interchangeably throughout the thesis and refer to the level measured by the twelve item General Health Questionnaire (GHQ-12), originally developed by Goldberg (1972). The GHQ is designed to reflect the mental health condition of respondents and is widely used for psychological assessment and measurement of mental-health. Previous studies such as Banks et al. (1980), Romppel et al. (2013) and Gelaye et al. (2015) have demonstrated the wide applicability and reliability of the GHQ as a measure of mental-health.

2.1.1 Research Motivation

The costs of unemployment includes lost output in the economy, loss of wages for the individual as well as the direct public subsidy costs of unemployment benefits. The often intangible social costs of unemployment associated with mental and physical health conditions are harder to calculate and is sometimes given less importance in the research, though these may be of a larger consideration. From a wellbeing perspective, these impacts include minor impacts such as loss of self-esteem to the more serious conditions that extend to diagnosed mental-health conditions such as depression. Previous research such as Chandola and Zhang (2017) suggests that health related impacts of unemployment extend not just on physical health, but importantly, the impact extends to mental-health as well.

Therefore, if the empirical evidence suggests that unemployment leads to lower levels of individual health, the overall costs of unemployment to the economy are likely to be much higher than originally thought. This research, thus aims to contribute to our understanding of labour market impacts on mental-health and expects to find relevance in designing appropriate labour market policies, which are mandated to mitigate the impact of unemployment on the general public.

2.1.2 Research Objectives

The primary objective of this research is to deepen our understanding of the nature of the relationship between labour market status and transitions with mental-health levels. The research initially investigates baseline mental-health scores associated with contemporaneous labour market status and subsequently the mental-health scores associated with transitions from one labour market status to the next. Specifically, the study also investigates the asymmetric impacts on mental-health stemming from labour market transitions and also checks for the presence of adaptation over time.

This chapter investigates the following research questions.

- **Research Question 1:** How are mental-health levels associated with contemporaneous labour market status and labour market transitions?
- **Research Question 2:** Are there asymmetric effect sizes on mental-health stemming from labour market transitions and their reverse transitions?
- **Research Question 3:** Do the empirical findings suggest the presence of adaptation to labour market shocks such as the event of unemployment?

It is expected that this research will contribute towards a better understanding of the relationship between labour market transitions and their association with individual mental-health levels. The results, although specific to the United Kingdom, are expected to be applicable in a wider setting.

2.2 Review of Literature

A vast amount of existing research already considers various aspects of the complex bi-directional causal relationship between unemployment and health. The present research attempts to contribute to the existing literature in this field through an analysis of the harmonised BHPS and Understanding Society household level survey data in the UK.

Previous studies such as Jackson and Warr (1984), Theodossiou (1998) and Bartley et al. (2006) that investigated the relationship between unemployment and psychological well-being find a clear association of unemployed individuals having lower levels of mental-health. Studies by Hamilton et al. (1990) and Martikainen et al. (2007) that analysed plant closures also reveal declining mental-health for individuals subsequent to job loss. Longitudinal studies such as Joelson and Wahlquist (1987), Dooley et al. (1994), Weich and Lewis (1998), Winkelmann and Winkelmann (1998), Montgomery et al. (1999) and Wadsworth et al. (1999) that investigated the relationship between mental-health and labour market transitions established the decline in mental-health following a transition from employment to unemployment and an improvement in psychological wellbeing for reverse transitions of unemployment into employment.

Clark and Oswald (1994) provide one of the first important analysis of unemployment and mental-health using the BHPS dataset by assigning individual caseness score based on their GHQ responses. While the paper serves as an important foundation for future research in the field, the study only considered associations between labour market status and mental-health in a cross-sectional analysis. Overcoming this limitation, Flint et al. (2013) use the same BHPS dataset but extend the analysis to investigate the predictive power of labour market transitions over mental-health, as defined by GHQ scores. The paper uses a fixed effects model and investigates transitions including between secure and unsecure employment. Though the paper establishes important findings in the field, similar to those found in Thomas et al. (2005), the possible methodological issues of selection effects and reverse causality were not addressed.

For the investigation of adaptation effects seen over time, resulting from the initial negative mental-health impacts of job loss and other significant life events, studies such as Frijters et al. (2011), Booker and Sacker (2012) and Clark and Georgellis (2013) provide important results of relevance to the present research. The findings show that individuals display signs of adaptation over extended periods of unemployment and other negative life events. Further Frijters et al. (2011), Grun et al. (2010), investigate into and establish the presence of asymmetry in mental-health impacts with labour market transitions and their reverse transitions. Notably, the negative impacts on mental-health from unemployment are seen to be stronger than the positive impacts from re-employment.

Several studies exploit the occurrence of exogenous unemployment to arrive at stronger causal estimates. Gallo et al. (2000) use a multivariate OLS regression model to address the methodological challenges of reverse causality and unobserved heterogeneity found in similar investigations to arrive at a significant causal relationship between involuntary job loss and physical and mental health among older workers. Similarly, Kassenboehmer and Haisken-DeNew (2009) analyse exogenous sources of unemployment to identify their significant causal effects on life satisfaction and also find important gender disparity in the results between men and women.

Finally, Murphy and Athanasou (1999), Paul and Moser (2009) and Modini et al. (2016) conduct meta-analysis of the existing literature covering the impact of labour market status and transitions on mental-health. The results of the meta-analysis showed the significant negative impacts on mental-health from unemployment and well as positive (but smaller) effects from re-employment. This finding reinforces the important result of the presence of asymmetry in mental-health impacts stemming from labour market shocks. The meta-analysis also covered a range of cross-sectional and longitudinal studies with more reliable causal inferences found in studies that exploited exogenous sources of unemployment. These are discussed in more detail in the next section.

The review of literature is divided into three sections. First, we cover studies where mental-health is the dependent variable with labour market status being the explanatory variable. We initially focus on papers that are closely aligned with the present research in terms of methodology and dataset used. Subsequently, we expand our literature review to cover the broader range of issues that previous research has discussed. Relevant papers that have investigated the impact of unemployment on physical-health are also included. Several of the papers reviewed use the BHPS or US dataset, but the combined dataset used in the present chapter allows for an investigation of a much longer period. Secondly, we look at studies that have conducted meta-analysis between labour market status and mental-health to get an overview of the results in this field. Thirdly, we also review studies where employment status is the dependent variable with mental-health levels forming the explanatory variables as this raises methodological challenges to consider for arriving at causal inferences in our conclusions.

2.2.1 Mental-Health as the Dependent Variable

Clark and Oswald (1994) provide a seminal analysis into the relationship between mental-health and unemployment using BHPS data from 1991 and assigning a caseness score to each individual based on the responses to the GHQ questionnaire. Notably, the paper finds that unemployed individuals have approximately double the mean mental distress scores of employed and self-employed individuals. Additionally, the results also show that unemployed individuals with higher education, people in their 30s, and women have lower levels of mental-health. The level of mental distress among the unemployed are also seen to reduce after 1 year and hint that the long-term unemployed are essentially less unhappy than those who are still in short-term unemployment. Further, individuals who are unemployed in a region with high unemployment rates show lower mental distress. Overall, the paper provides an important foundation on which a large literature of future research on the relationship between mental-health with labour market status and transitions evolved.

Flint et al. (2013) examines data from the British Household Panel Survey over 1991 to 2007 to investigate if labour market transitions have significant predictive power over mental well-being as defined by GHQ scores. The study uses fixed effects models to investigate the transitions between labour market status such as secure employment, insecure employment, unemployment, economic inactivity and long-term sickness and their effects on well-being after controlling for standard socio-economic factors known to affect individual well-being. Initially, labour market status was regressed on GHQ scores to get an idea of the baseline GHQ scores associated with each labour market status, with secure employment as the reference category. Next, labour market transitions were regressed upon GHQ scores to investigate their effects on wellbeing levels. Causal inference was then investigated by comparing the estimated effects of labour market transitions with the estimated effects of the contemporaneous labour market status. Jointly interpreting the two sets of coefficients showed the impacts that labour market transitions had in addition to the baseline effects. The results indicated a causal relationship between labour market status and mental well-being. It was seen that a transition from both secure and insecure employment into unemployment as well as into long-term sickness had significant effects leading to lower mental-health levels. However, the reverse transitions for both cases was found to have a positive impact on mental-health but with smaller effect sizes. Notably, while the study acknowledges the difficulties associated with the individual interpretations of the definitions of secure and insecure employment as a methodological drawback, the possible issues of selection effects and reverse causality was not addressed in the study.

Gielen and Van Ours (2014) investigates further into the seemingly inconsistent results found in the empirical literature that investigated the relationship between wellbeing and labour market status of unemployment and reemployment. While several studies including Clark and Oswald (1994), Winkelmann and Winkelmann (1998) and Kassenboehmer and Haisken-DeNew (2009) show that unemployed individuals are unhappy compared to their employed peers, other studies such as Abbring et al. (2005), Graversen and Van Ours (2008), Graversen and Van Ours (2011) and Arni et al. (2013) also reveal that government sponsored ALMPs are often necessary and to push the unemployed into reemployment. The authors hypothesise that given the drop in happiness experienced by job loss, individuals should be naturally incentivised and willing to find jobs on their own instead of requiring participation in labour market programmes. Using longitudinal unemployment duration data from the German Socio-Economic Panel from 1994 to 2007, the study investigates further into the seemingly puzzling requirement for ALMPs to stimulate reemployment among the unemployed. The authors find that although the unemployed experience a drop in happiness consequent to job loss, this result is subject to a wide variation. Over half of the unemployed do not experience a drop in their life satisfaction levels and therefore require some activation to re-enter the labour market. The study also finds evidence of a scaring effect whereby unemployed individuals that experienced a drop in life satisfaction, reemployment does not lead to a full recovery of their life satisfaction levels.

Thomas et al. (2005) use the first eight waves of the BHPS to investigate how transitions to and from paid employment affect mental health measured by GHQ scores. They also investigate the mental-health levels associated with various other labour market states reported in the BHPS and if the results vary greatly for men and women. The study uses a multivariate logistic regression model and calculates odds ratios to calculate the likelihood of having poor mental-health. The paper defines instances where GHQ scores were higher than the mean as cases where mental-health levels have deteriorated. To control for baseline health, the GHQ scores prior to the transition and long-term sickness status was added to the model. It was found that, for those moving into employment from being non-employed and for those remaining employed, the number of higher than average GHQ cases fell the most. Also, the higher number of cases with above mean GHQ scores for those remaining non-employed in the previous time period, suggested likely health selection effects. The findings suggest that, while transitions from employment into unemployment & long-term sickness are associated with lower mental-health, the reverse transitions into employment are associated with improved mental-health.

Frijters et al. (2011) conduct an investigation into how well individuals are able to adapt their life satisfaction levels from the impact of positive and negative life events. Using quarterly panel data from the Household, Income and Labour Dynamics in Australia survey, the authors evaluate the impact on life satisfaction from various substantive life events such as marriage, separation, death of partner or child, victim of crime, job loss, and a major improvement or worsening of financial situation. The authors identify and estimate three effects that individuals are likely to face with respect to the above life events. These include, the anticipation effect (impact on life satisfaction from event before occurrence), the adaptation effect (impact on life satisfaction from event after occurrence), and the selection effect (comparison of life satisfaction of those who experienced the event vs those that did not). Interestingly the paper notes the presence of all three effects, raising challenges to proper estimations using only cross sectional data as selection effects are unable to be identified accurately. As well as possible underestimations of the anticipation and adaptation effects when using yearly lags and leads in the data. The paper also finds evidence of asymmetry in the impacts on life satisfaction from death vs birth and in case of a deterioration vs improvement of financial position. In both cases, the negative impact was seen to be stronger than the positive impact. Based on the analysis, the paper also proposes a new method to compensate individuals by valuing the impact of life events.

Booker and Sacker (2012) use a multi-level modelling approach to investigate the effects of multiple unemployment spells on well-being. The study classifies individual unemployment for a single spell, two spells and over three spells in the observation period as variables of interest and tests for signs of adaptation or sensitisation. The dataset used consists of 17 waves of the BHPS and the measure of well-being used is the GHQ 12. The study also considered the previous labour market status of individuals, specifically whether they were in employment or economic inactivity prior to unemployment. The results showed that while unemployment was seen to have a detrimental impact on mental wellbeing with the effect increasing over time, the consideration of previous labour market status was also relevant. Previously employed individuals showed poor levels of mental health for the first two spells of unemployment, but showed improvement in the third spell. However, economically inactive individuals showed increased deterioration in mental-health levels by the third spell. Thus, the study leads to the inference that adaptation to detrimental well-being effects stemming from unemployment exist for previously employed individuals while those transitioning out of economic inactivity and unable to gain employment tend to face sensitisation effects.

Clark and Georgellis (2013) analyse 18 waves of the BHPS data to assess the impact of major life events on self-reported life satisfaction scores and GHQ 12 scores. The life events considered include unemployment, marriage, divorce, birth of a child and widowhood. Using the panel data available over 18 years, the study follows individuals transitioning into the first occurrence of any life event of interest and check to see how individuals anticipate and adapt to these events over long periods of time. In the case of unemployment, the results for both life satisfaction and GHQ-12 variables are found to be similar. The significant negative effects on subjective wellbeing persists for five years after unemployment for men, though in the case of women this is limited to two years. Beyond five years, this effect continues to be negative for men, though no longer significant. The results are similar to Clark et al. (2008) which analysed 20 waves of the German Socio Economic Panel and revealed significant lag and lead effects for both men and women.

Schmitz (2011) analyses the German Socio Economic Panel data for the period 1991 to 2008 to investigate if causality between unemployment and lower levels of health can be established. Three measures of health are used in the model, this includes self-reported satisfaction with health, a summary scale representing mental-health questions and a binary variable for overnight hospital stays. The study uses both OLS and fixed-effects models incorporating ordered logit and logit after identifying plant closures as exogenous entries into unemployment. The main finding is that while unemployment is negatively associated with health, exogenously caused unemployment did not have a deteriorating effect on health. Although, as acknowledged in the study, this observed association may be biased on account of selection effects. The results however are specific to Germany where unemployment benefits are generous and loss in income from unemployment is moderate.

Broom et al. (2006) investigates the health benefits of paid work versus unemployment in Australia. The study takes information on depression, physical health, self-rated health and doctor visits as health measures and differentes job quality based on strain, job insecurity and likelihood of finding another job. The analysis is based on a primary survey of approximately 2500 adult individuals. The study finds that those unemployed have reported far worse health scores when compared to those with jobs. However, job quality is found to be significant in the analysis on health. Unemployed individuals did not report worse off health measures as compared to those with poor quality jobs. The results raise an important challenge to the notion that finding any job is associated with better levels of health than for those without a job.

Schuring et al. (2010) uses linear regression to investigate the influence of re-employment on changes in perceived health by looking at unemployed individuals that received unemployment benefits but were capable of full-time employment and subsequently moved back into employment. The study uses a cox proportional hazards analysis to determine the factors that are significant for predicting re-employment. The results show that baseline health status of the participants were an important factor for being re-employed, suggesting selection effects in the panel. Individuals in good health at the start had a much higher likelihood of returning to paid employment, lending credibility to the selection hypothesis. Further, among those re-employed, self-perceived health scores showed improvements in the shorter term, supporting the causation hypothesis that mental and physical health improves post re-employment.

Grun et al. (2010) analyses the impact on life satisfaction while transitioning from unemployment to full-time employment taking in account the effect of job quality using data from the German Socio-Economic Panel. The definition of job quality encompasses both objective parameters such as wages, working hours and type of work contract, as well as subjective parameters such as job satisfaction in the analysis but these are tested for separately due to the high correlation between both. The analysis used fixed-effects conditional logit model framework for analysing influence of job quality on life satisfaction and controlled for the influence of standard socio-economic factors. The results show that the positive effect on life satisfaction is present for almost all dimensions of job quality. However, the effects are not significant in the case of being employed in jobs with very low self-reported job satisfaction. To examine the impact of re-employment, the study combines job quality variables into an index and compares the life satisfaction from the current job with that of the previous job. It was seen that the positive effects of job quality on life satisfaction are also significant but the effect size is much lower when the new job is worse than the previous job. The beneficial effects of re-employment on life satisfaction are also seen to persist into the second year of re-employment which implies the absence of negative adaptation that may have caused life satisfaction levels to revert to original unemployed levels.

Gallo et al. (2000) investigated the health effects of involuntary job loss specifically among older workers aged 51 to 61 and found a causal relationship between job loss and lower levels of both physical functioning and mental health. The study uses data from 2 waves of the Health and Retirement Survey in the United States and applies OLS regression to test for the impact of job loss on health. Involuntary job losses were identified as those being caused by plant closures and layoffs. The study acknowledges the possibility of endogeneity on two possible sources. These include, firstly, possible reverse causality where deteriorating health may be the cause of involuntary job loss This was addressed using a two-step method by initially regressing the dummy variable for involuntary job loss on baseline health, the exogenous variables and an instrumental variable of Unemployment Insurance to calculate the residuals. The estimated residuals were then included as an additional regressor in the final regression. The coefficients of these residuals were found to be insignificant, which implied that involuntary job loss was not endogenously determined. The second possible issue with the model was on account of unobserved heterogeneity which was addressed by careful choice of the analysis sample and the use of comprehensive control variables including a measure of baseline health. The study results confirm the statistically significant negative association of involuntary job losses to physical and mental health in the case of older adults. Further, re-employment is seen to be significantly positively associated with physical and mental health. However, the possibility of reverse causality remains because health parameters were not assessed after the initial involuntary job loss and prior to re-employment for workers who faced a loss in employment between the interviews.

Kassenboehmer and Haisken-DeNew (2009) analyses data from the German Socio Economic Panel from 1984-2006 and investigates the impact of unemployment on life satisfaction. The study divides the dataset into sub-samples of East and West Germans for men and women, and examines exogenous variation in unemployment to identify causal effects. The estimation methods include, pooled OLS regression, linear fixed-effects, pooled logit and conditional logit. The dataset allowed for the identifying voluntary unemployment and exogenous entries of unemployment in the case of a company closure. However, getting fired by the employer was kept as a separate variable on account of the fact that some individuals may choose to get fired instead of quitting voluntarily to receive compensation. The study finds significant negative effects of unemployment on life satisfaction across all methodologies. Further, investigation of the reason for entry into unemployment finds that exogenous entries into unemployment are also significant with negative impacts on life-satisfaction. Notably, the estimated effects in the case of voluntary unemployment are found to be insignificant. The results are especially significant for women, more so in East Germany, who face significant negative life satisfaction on account of unemployment. This suggests gender disparity in the effects of unemployment on life satisfaction.

Browning et al. (2006) investigates the link between unemployment and health taking data from 1981 to 1999 in Denmark covering 10% of all males in the country. The study examines cases of displaced workers from plant closures that laid off more than 30% of its workforce and whether this displacement has a causal effect on hospitalisation for stress related diseases. The likely presence of selection effects makes a direct comparison of displaced workers with non-displaced workers unreliable. Instead, the study uses propensity score matching to match the sample of displaced workers as a treatment group, with non-displaced workers as a control group, using the closest propensity scores based on a linear index. The average treatment effect on the displaced is estimated with respect to the control group of non-displaced individuals, after controlling for individual socio-economic characteristics and initial health status. The results indicate that the effect of being displaced causes almost no effect on hospitalisation for stress related diseases and is insignificant. Further analysis also shows that the results do not vary for any specific age groups. However, the findings are thought to be applicable for only Scandinavian countries where a relatively strong safety net through unemployment insurance exists.

Böckerman and Ilmakunnas (2009) examines the relationship between unemployment and self-assessed health in Finland during 1996-2001 in a panel data setting. The study investigates the self-assessed health prior to and after unemployment and subsequently after re-employment to test for causal effects of unemployment on health. The study looks at individuals who encountered transitions into and out of employment from unemployment with the reference category as those that remained in employment. By applying a difference in differences model and matching method the study also takes into account the possibility of reverse causality of health on unemployment. Cross-sectional information shows that those ending up unemployed have lower levels of health compared to those who remain employed, hence the pool of unemployed consists of individuals with lower levels of health. Thus, negative selection accounts for the association of poor mental-health and unemployment. This result is however, not found longitudinally. The study undertakes ordinary least squares, fixed-effects, ordered logit, fixed-effects ordered logit and random-effect ordered probit estimation methods to check the causal effect over time for unemployment on health. A robustness check of the results with propensity score matching confirms that the event of unemployment does not matter for self-reported levels of health over time.

Ahn et al. (2004) uses data from the European Community Household Panel survey from 1994 - 2001 and examines the effect of unemployment on five self-reported factors that contribute to a measure of wellbeing. The survey extended across western European countries and consisted of self-assessment questionnaires, including the five topics of wellbeing used for the research. The study identifies work, financial situation, housing, leisure time and health as important domains of wellbeing. Noting that unemployment is likely to reduce income but increase time spent in leisure, the study aims to investigate the impact of unemployment on the five aspects of wellbeing. Initially, the study takes a pooled cross section sample of all waves to investigate the association between employment status and average levels of wellbeing. The results showed that the unemployed suffer reduced satisfaction in all aspects of wellbeing except leisure time when compared to employed individuals. Moving to a panel setting, the study compares the changes in wellbeing levels with changes in employment status. The four possible transitions between employment and unemployment, including remaining in each category, are considered. The results confirm with that of the cross-sectional data, showing that movement into unemployment reduces wellbeing on all aspects except leisure time. In addition, moving from unemployment into employment increases wellbeing, except for leisure time. Socio-economic controls are applied to the OLS regressions used for the analysis, but the overall results are likely to be biased to some degree on account of the fact that all five domains of wellbeing used in the study are endogenous. The study explicitly acknowledges this possibility of an endogeneity bias. There is, however, a large variation in the results between the various countries in the survey and this is likely an indication of the differences between the unemployment benefit systems in each country.

Backhans and Hemmingsson (2012) investigates the relationship between unemployment and mental-health based on GHQ scores to test if quality of employment is a differentiating factor and how the estimated impacts compare between social and demographic groups. The study used data from the Stockholm county council Public Health Survey from 2002 to 2006 with a final sample size of over 12,000 respondents in a logistic regression framework to assess the impacts. Socio-economic controls and previous health status was adjusted for as well in the model. In order to reduce the selection effects, individuals who were unemployed prior to 2002 are excluded from the sample. The data was grouped by age, sex, family situation, socio-economic position and working environment, and the results analyse the differences found in these groups. The results show that the impact of unemployment on mental-health is more pronounced among men, overtime workers and the self-employed. Unemployment duration is also found to be associated with lower levels of mental-health.

Frijters et al. (2005) analyses the relationship between income and health satisfaction using data from 1984 to 2002 between East and West Germany. The authors acknowledge the difficulty of disentangling cause and effect on account of unobserved individual heterogeneity and endogeneity leading to reverse causality. The authors use the fall of the Berlin wall as an exogenous positive shock to income for East Germany. Using fixed-effects ordinal logit models for men and women separately, a number of covariates are controlled for. The results show that positive income change has a very small but significant positive effect on health satisfaction for East German men while the income effect on health satisfaction extends to both men and women in West Germany.

Kuhn et al. (2009) acknowledges the difficulty of assessing the causal effect of job loss on public health costs because poor health can also be a cause of job loss. The study analyses the causal effect of job losses (induced by plant closures) on public health expenditure in Austria. This removes the potential bias of reverse causality by keeping the reason for job loss as exogenous. Relevant to the analysis is the fact that Austrian health care covers both medical costs as well as temporary incomes for those unable to work due to health reasons. The methodology involves defining a treatment group for employed at a firm that suffers plant closure and the control group as those employed in a firm where plant closure did not occur. Each treated individual in the randomised control is matched to an untreated individual using propensity score matching. The average causal effect of unemployment from plant closure on public health costs is measured to arrive at the average treatment effect for the treated. The empirical results indicate that plant closure induced job losses do not cause a significant increase in public health costs related to hospitalisations, doctors visits and drug prescriptions. An increase in public health costs associated with mental-health in terms of anti-depressant prescription drugs and hospitalisation is seen in the case of men, after plant closure. Health care costs related to sickness benefit incomes increase significantly after a job loss, though structural reasons related to incentives were identified for this effect. Finally, a sensitivity analysis confirmed the results that the overall increase in public health costs following job losses is from sickness benefits alone.

Chandola and Zhang (2017) use the first three waves of the Understanding Society household survey data to investigate if individuals being re-employed in lower quality work have better health levels than their peers that remain unemployed. The study identifies unemployed individuals in wave 1 who are actively looking for work to assess the health impacts of employment into low quality jobs on health versus remaining in unemployment. Health outcomes were measured using stress-related biomarkers and self-reported health scores. A measure of job quality was derived using the reported variables on job satisfaction, job anxiety, job autonomy, job insecurity and job pay. Socio-economic controls were also added into the multinomial logit model. The study finds that, unemployed individuals that transitioned into poor quality jobs had worse off levels of health in their biomarkers as compared to those that remained unemployed. The evidence suggested that quality of work has important implications for health and wellbeing.

2.2.2 Meta Analysis of the effect of Unemployment on Mental-Health

Murphy and Athanasou (1999) analyses sixteen longitudinal studies from various countries between 1986 and 1996 to examine if variations in employment status affects mental-health. The objective of the meta-analysis was to arrive at an understanding of the relationship and the associated effect sizes on mental-health stemming from labour market status changes. The reviewed studies predominantly used self-reported mental-health variables of wellbeing such as GHQ and depression related variables in some. The reviewed studies show evidence pointing to the existence of a significant relationship between employment and mental-health. These included both, the positive effects of gaining employment and the negative effects of losing employment upon mental-health. However, the issue of selection bias is identified as a potential area of concern while interpreting the results. The meta-analysis also looks at the effect sizes of moving into employment and unemployment on mental-health across the reviewed studies. While the evidence confirmed positive effects of employment and negative effects of unemployment on mental-health, the magnitude for both groups varied. The weighted average effect size on mental health for transition from unemployment into employment was calculated as 0.54 with a total of 1509 participants across 10 studies. The weighted average effect size for transitions from employed to unemployed was estimated at 0.36 but the 5 studies reviewed had a total of only 616 participants. Care must be taken for interpreting these results due to the inherent drawbacks of combining the empirical results of various studies together. However, the meta-analysis is useful to the extent that it demonstrates the presence of asymmetry in the effect sizes for labour market transitions and their reverse transitions.

Paul and Moser (2009) conducts a detailed meta-analysis on the effects of unemployment on mental-health across both cross-sectional and longitudinal studies. The study reviews over 320 existing publications between 1963 and 2004 on the topic. The large number of papers reviewed meant that mental-health was defined broadly to include various measures of subjective wellbeing to depression and other psychosomatic symptoms. Notably, the study also looks at the moderators applied across the full sample of reviewed papers. The meta-analysis finds gender, occupation, marital status, age, unemployment duration, income, unemployment benefits and year of data collection as relevant socio-economic controls for mental-health. The issue of negative selection is identified as being a central challenge to interpreting the results of causality for unemployment and mental-health. At the cross-sectional level, the meta-analysis finds evidence to show that unemployed individuals have higher levels of mental distress than their employed counterparts. The meta-analysis of longitudinal studies showed that transitions from employment to unemployment and its reverse, were associated with negative and positive mental-health effects, respectively. However, studies where exogenous events of unemployment such as plant closures were used, stronger and more reliable causal inferences are found.

Modini et al. (2016) conducts a meta-review of the existing meta-analysis literature on the potential mental-health benefits of employment. Through careful screening of the papers selected, the papers were short-listed by screening the abstract and titles and again by screening the full texts and assigning a quality score for the methodology used. The final selected papers included reviews concerning employment effects on mental-health outcomes in USA, Germany, UK, Canada, Australia and Sweden. The meta-review only focussed on papers that reviewed the impact of employment on mental disorders such as depression and not self-reported wellbeing, which would have had a wider application. Overall, the results indicate that while the negative impact of unemployment on health is evidenced in many of the studies, it is also seen that work can be beneficial to mental-health. Having a job is associated with a range of improved mental health outcomes including reduced depression and anxiety symptoms and enhanced social status. Specifically, the evidence supports the hypothesis that employed and re-employed individuals encounter better levels of mental-health through improved social status, increased access to resources and work place interactions.

2.2.3 Unemployment as the Dependent Variable

Arrow (1996) uses data from the German Socio-Economic Panel from 1984 to 1990 to investigate the negative health selection hypothesis that because unhealthy individuals are more likely to lose employment or face hurdles to gain re-employment, the proportion of unhealthy individuals among the unemployed will be higher than among the general population. The study uses multivariate regression with cox proportional hazard analysis to model the logged survival rate of employment and investigates if lower levels of health are associated with lower employment duration. Subjective measures of health as well as information relating to chronic illness and long sick leaves are used as independent variables. The study also tests to see if gender and nationality has an influence on the overall results. The main finding is that health factors in general do not increase the probability and duration of unemployment for employed individuals. However, poor health finds significance as a risk factor to employment in concurrence with other factors such as chronic illness and long absence from work for health reasons. The estimated effects vary across different types of workers and the result was seen only in the case of female workers and foreign workers. Additionally, it was also seen that previous unemployment spells increased the risk of recurrent unemployment.

Butterworth et al. (2012) investigates how mental-health plays a role in influencing future employment status. The study uses five waves of the Household, Income, Labour Dynamics in Australia survey to examine if baseline mental-health predicted the risk of any subsequent unemployment experience. The study also examined if baseline mental-health predicted the duration of unemployment for those who were unemployed at any time in the study. Self-reported mental-health was normalised on a 0 to 100 scale and used as independent variables in the negative binomial, logit and zero truncated negative binomial regression models. The regression models examined if baseline mental-health could predict the risk of subsequent unemployment and the duration of unemployment for individuals who had already reported being unemployed. However, the study acknowledges the possibility of reverse causality where unemployment could be a cause of lower levels of mental-health. A sensitivity analysis also checked the robustness of the results. The results showed that poorer mental-health at the baseline translated into greater duration of unemployment for men and women and an increased risk of experiencing subsequent unemployment for women.

García-Gómez et al. (2010) use twelve waves from the British Household Panel Survey to analyse the impact of health on employment entries and exits. The study uses several measures of self-reported health. Firstly, dummies representing various medical conditions such as diabetes, depression, anxiety etc. are generated. Secondly, a measure of self-reported health if an individual is limited in daily activities. Thirdly, with the use of GHQ scores that measure mental-health. The methodology uses discrete-time duration models to estimate the effect of health on the hazard of becoming non-employed and employed. Three different samples are used. Namely, those that are working in the first wave, non-working in the first wave and those that stop working. The results show that deteriorating levels of health are associated with an increase in the hazard of non-employment for the sample of workers. The evidence suggests that health has a significant predictive power over employment transitions, with higher effects on men than women. However, a limitation of the research is that all individuals who were non-employed were grouped into a single category, which could have resulted in generalised conclusions that may not hold for certain specific labour market states.

2.3 Data and Methodology

This section explains the data and methodology for the present research. An overview of the panel dataset and variables used are first provided and subsequently the empirical strategy employed is elaborated. The research methodology for this chapter closely follows Flint et al. (2013) and Thomas et al. (2005) while also keeping in mind findings from Murphy and Athanasou (1999) and Paul and Moser (2009).

2.3.1 Description of the Dataset

The British Household Panel Survey (BHPS) and the Understanding Society (US) longitudinal survey are the main datasets used for the present research. Both surveys were conducted by the Institute for Social and Economic Research (ISER) at the University of Essex. The nature of the BHPS survey is that of longitudinal household interviews conducted every year from 1991 until 2008 in the UK. This generates a total of 18 waves of data covering various aspects of life such as income, work, health, well-being, education and other socio-economic and demographic aspects of individuals. The BHPS helps improve our overall understanding of social and economic conditions faced by the UK population. The BHPS initially incorporated a randomly selected sample of over 5,000 households in the UK based on a stratified cluster design drawn from the Postcode Address File[1]. Each adult member of the selected sample of households were interviewed face to face. An adult interview lasted approximately 45 minutes along with an additional household level questionnaire that was answered by one adult in each household[2]. The individuals present in the selected households were followed every successive year and re-interviewed. In case the same individuals moved away from the original household to form new households, they were followed and all adult members of the new households were interviewed as well. Additionally, all individuals who joined the original sample of households were also added to the interview list. This has provided researchers with a multi-dimensional longitudinal dataset that comprises both individual level and household level observations.

From 2009, the BHPS was discontinued and the US longitudinal survey was implemented in the UK. The US survey incorporated over 40,000 households in wave 1 that began in 2009[3]. Seven waves of the US survey are used in the present research. Although each wave of the US survey began in each year subsequent to 2009, the surveys have taken more than a year to complete. This generates an overlap in the dataset in terms of the time-line[4]. For the purposes of this research, the year in which the actual interview took place is taken as relevant, regardless of when each wave concluded.

The original datasets which included the 18 separate waves of the BHPS from 1991 to 2007 were edited by choosing select variables relevant to the present research and appending the variables vertically over all the waves. The same exercise was conducted for the US dataset for 7 waves extending from 2009 to 2017. The variables chosen between both datasets were compared and those incompatible with both datasets were dropped. The remaining variables gives us data over 25 waves and was renamed to match with the US dataset to maintain convenience in the event that new waves are available to be added to the research dataset in the future. The selected waves across the BHPS and US dataset was combined for a total of 25 waves into a single longitudinal panel.

[1]https://www.iser.essex.ac.uk/bhps/about/sample
[2]https://www.iser.essex.ac.uk/bhps/about/questionnaire-content
[3]https://www.understandingsociety.ac.uk/documentation/mainstage
[4]https://www.understandingsociety.ac.uk/documentation/mainstage/survey-timeline

The final dataset used for the present research is the Harmonised BHPS and Understanding Society panel which incorporates over 25 years of longitudinal data on the general population of the UK. The harmonised BHPS-US dataset has streamlined general issues such as naming conventions of variables to account for all the years, spurious matches in case of different variables having the same name and ensuring that variables that were named differently in both panels have been renamed to ensure consistency[5]. Overall the harmonisation of both datasets undertaken by the ISER has brought about a reliable degree of compatibility between both datasets that allows us to investigate impacts over a quarter century of social data. Thus, we are able to investigate the topic of this research; the impact of labour market transitions on mental-health.

2.3.2 Data Cleaning Methodology

The BHPS and US harmonised datasets were downloaded from UK Data Service in dta format for use in Stata. Variables selected for the present research were extracted from each wave of the BHPS and US datasets. The variables were renamed for consistency across the BHPS and US datasets along with a wave identifier for future use and appended into a single dta file that represented 27 years of panel data. The variables selected were drawn from the individual response files as well as the household response files of the BHPS and US datasets. Across all variables the missing observations, refusal of answers, inapplicable and proxy responses were also recoded as missing values.

The combined panel representing 25 waves was then subjected to various data cleaning techniques to achieve the consistency required for further research and investigation of the impact of labour market transitions on mental wellbeing. Minor trimming of the dataset for individuals below the age of 16 and above the age of 65, as well as assertion tests to ensure that data cleaning procedures were error free were also conducted. The details of the occurrence of each variable across all Waves are provided in Appendix A.1.1.

The final analytical sample used for the research included 392,828 observations on 88,523 unique individuals over the 25 waves. The dataset contains individuals that are present from a single wave to a maximum of eighteen consecutive waves over the entire panel. The extent of attrition seen as a percentage from one period to the next in the panel is presented below in Table 1 and shows an unbalanced panel to an expected degree over 25 waves. The merging of the BHPS and US dataset in Wave 19 shows 100% attrition from Wave 18 to Wave 19 and this is to be expected within the panel design as noted by

[5] https://www.understandingsociety.ac.uk/sites/default/files/downloads/documentation/mainstage/user-guides/bhps-harmonised-user-guide.pdf

(US, 2017, p7), *"Data for the BHPS samples participating in Understanding Society is collected in the first year of each wave, starting from Understanding Society Wave 2".*

Table 1: **Sample Attrition Rates by Wave**

Wave Number	No of Individuals	No of Individuals in Next Wave	No of Attrition	% of Attrition
Wave 1	7999	6732	-1267	15.8
Wave 2	7681	6532	-1149	15.0
Wave 3	7427	6561	-866	11.7
Wave 4	7462	6522	-940	12.6
Wave 5	7261	6623	-638	8.8
Wave 6	7547	6758	-789	10.5
Wave 7	8721	7740	-981	11.2
Wave 8	8516	7589	-927	10.9
Wave 9	12048	10494	-1554	12.9
Wave 10	12114	10612	-1502	12.4
Wave 11	14396	11185	-3211	22.3
Wave 12	12410	10726	-1684	13.6
Wave 13	12170	10390	-1780	14.6
Wave 14	11573	10192	-1381	11.9
Wave 15	11571	10152	-1419	12.3
Wave 16	11249	9789	-1460	13.0
Wave 17	10860	9307	-1553	14.3
Wave 18	10234	0	-10234	100.0
Wave 19	32099	20603	-11496	35.8
Wave 20	33605	24365	-9240	27.5
Wave 21	31662	24185	-7477	23.6
Wave 22	29630	22941	-6689	22.6
Wave 23	27518	20468	-7050	25.6
Wave 24	28804	22474	-6330	22.0
Wave 25	28271	NA	NA	NA

Central to the need of ensuring representativeness of the sample are decisions concerning the use of weights in the sample dataset as well as the choice of inclusion or exclusion of sample boosts separately available in the Understanding Society survey. As elaborated by US (2020) the goal of ensuring representativeness of the sample are for enabling population inferences and to ensure sufficient heterogeneity in the sample. The period of the analysis of this research extend from 1991 to 2017 and by design, the dataset aims to represent the evolving population of the UK, through this period. There is a need to avoid excess benchmarks at any single point in time that may not correspond to the longitudinal population of interest.

The BHPS and US datasets provide weights that may be used separately while assessing different subpopulations of interest. The use of weights was considered but decided to be dropped as a consequence of the research interest being the impact of labour market status and transitions on mental-health for the general population in the UK during the period under study. The harmonised version of the dataset with the General Population Sample, which is the data being used, is already calibrated for general purpose research such as the present use case.

Both the BHPS and US survey have had extensions and boost samples added to the original sample throughout the course of their implementation. The original BHPS sample, which commenced in 1991 with 5050 households, had an additional low-income sub-sample of 1000 households added during 1997 to 2001. Further, the BHPS also incorporated a Welsh extension and Scottish extension of 1500 households each from 1999. Additionally, a Northern Ireland extension of 1900 households from 2001 was also a part of the BHPS.

The US survey initially commenced with a General Population sample of 26,000 households from the UK in 2009. This included England, Scotland, Wales and Northern Ireland. In 2010, the sample of BHPS respondents were also included into Wave 2 of the US survey. Additionally, the US survey also incorporated two boost samples. The Ethnic Minority Boost Sample of 4000 households in 2010 and the Immigrant and Ethnic Minority Boost Sample of 2900 households in 2015.

The use of extensions and boost samples aim to help improve the representativeness of the said subpopulations within the survey and dataset. However, in the case of the present research we are primarily interested in the impact of the labour market transitions on mental-health, over a long period spanning 25 years. Proper harmonisation of both the US and BHPS datasets are important to ensure consistency and reliability of the present results. The inclusion of these extensions and boost samples would not necessarily have improved the statistical representativeness of the sample and could potentially lead to a bias in the research sample.

Therefore, we limit the analysis in this research to the use of the General Population Sample of both the BHPS and US surveys that has been harmonised and provided for research by the UK Data Service.

2.3.3 Variables Selected and Descriptive Statistics

A brief explanation of each of the variables selected for the research and their descriptive statistics are explained below.

Dependent Variable

The 12 item General Health Questionnaire (GHQ-12) is an adapted version of the original General Health Questionnaire that was developed by Goldberg (1972). The GHQ-12 conducts an assessment of mental-health conditions of respondents through self-assessment questions and has been widely used for screening and measuring psychological wellbeing in a wide range of previous studies including Banks et al. (1980), Romppel et al. (2013) and Gelaye et al. (2015). The GHQ-12 has been a part of the BHPS and Understanding Society survey and is therefore available to be used as a measure of individual mental-health levels in the research sample. As shown by Pevalin (2000) the GHQ-12 is both consistent and reliable as an instrument for the measurement of mental-health, especially when applied to general population samples under both panel data and cross sectional data settings.

The GHQ variable comprises 12 different questions as shown below.

- A) *Have you recently been able to concentrate on whatever you are doing?*
- B) *Have you recently lost much sleep over worry?*
- C) *Have you recently felt that you were playing a useful part in things?*
- D) *Have you recently felt capable of making decisions about things?*
- E) *Have you recently felt constantly under strain?*
- F) *Have you recently felt you couldn't overcome your difficulties?*
- G) *Have you recently been able to enjoy your normal day-to-day activities?*
- H) *Have you recently been able to face up to problems?*
- I) *Have you recently been feeling unhappy or depressed?*
- J) *Have you recently been losing confidence in yourself?*
- K) *Have you recently been thinking of yourself as a worthless person?*
- L) *Have you recently been feeling reasonably happy, all things considered?*

The scoring for each of the GHQ variables follow a Likert Scale from 1 to 4 score as represented below.

I. **Question A**

1. *Better than usual*
2. *Same as usual*
3. *Less than usual*
4. *Much less than usual*

II. **Questions B,E,F,I,J,K**

1. *Not at all*
2. *No more than usual*
3. *Rather more than usual*
4. *Much more than usual*

III. **Questions C,D,G,H,L**

1. *More so than Usual*
2. *About the same as usual*
3. *Less so than usual*
4. *Much less than usual*

Comparing the above GHQ-12 questions and their scoring based on Likert Scale, it can be seen that the GHQ-12 questionnaire is split into positive and negative phrased items. As cautioned by Hankins (2008a) and Hankins (2008b) the negatively phrased items are prone to a higher response bias and therefore may be subject to measurement errors.

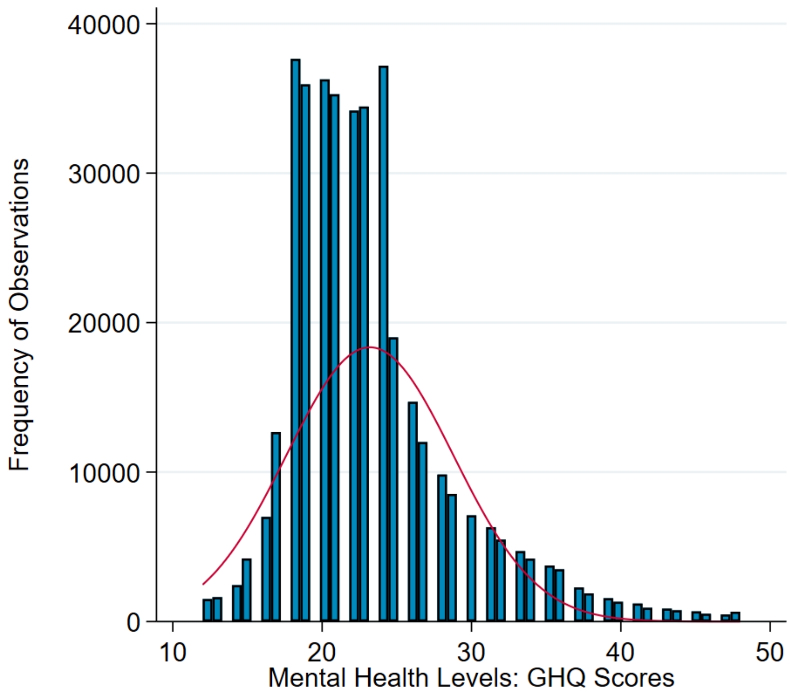
The GHQ-12 variable leads to an inverse score for mental-health wherein a higher score represents a lower level of mental-health. The 12 GHQ variables were combined into a newly derived variable that represented the total GHQ score which is the primary dependent variable of this research. All 25 waves of the harmonised BHPS and US dataset have the GHQ variable present in the questionnaires. The summary statistics for the derived dependent variable representing total GHQ score is given below in Table 2.

Table 2: **Summary Statistics for Total GHQ Scores**

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Mental Health Level	392,828	23.20	5.590	12	48

The normality of total GHQ scores was also examined as plotted below in Figure 1. We see that the distribution of the mental-health variable ranges from 12 to 48 with a mean score of 23.2. However, the data shows a higher level of kurtosis which means that some values within a certain band of GHQ scores have higher frequency than others.

Figure 1: **Distribution of Total GHQ Scores**



Source: Harmonised BHPS & Understanding Society Survey.

Independent Variables - Job Status Variables

The primary independent variable of the research derives from the Job Status variable found across all waves of the harmonised BHPS and US dataset. The exact question for the Job Status Variable is as follows.

Please look at this card and tell me what best describes your current employment situation?

The individual responses included all the below possible labour market states and was captured in the survey using the number scoring scale shown below.

- 1 *Self-employed*
- 2 *Employed*

- 3 *Unemployed*
- 4 *Retired*
- 5 *Maternity Leave*
- 6 *Family Care*
- 7 *Full Time Student, School*
- 8 *Long term Sick, Disabled*
- 9 *Government Training Scheme*
- 10 *Unpaid worker in family business*
- 11 *Working in Apprenticeship*
- 97 *Other*

All possible labour market status and their lags were recoded as individual dummy variables, allowing us to derive the labour market transition variables that are used in the research. The descriptive statistics of the job status variables in the harmonised BHPS and US panel is as below in Table 3 and frequencies are provided in Appendix A.1.2.

Table 3: **Descriptive Statistics of Job Status Variables**

Current Job Status	**Male %**	**Female %**
1 Self Employed	12.53	4.89
2 Employed	61.74	57.38
3 Unemployed	7.04	4.39
4 Retired	4.85	6.86
5 Maternity Leave	0.01	1.15
6 Family Care	0.70	13.04
7 Full Time Student	8.21	8.01
8 Long Term Sick / Disabled	4.59	4.02
9 Govt Training Scheme	0.25	0.17
10 Unpaid Worker in Family Business	0.02	0.05
11 Apprenticeship	0.07	0.04
Total	**100.0**	**100.0**

Further, the dummy variable of employed and self-employed were combined to create a derived binary variable representing a state of being in either employment or self-employment. The additional job status dummy variables created included retired, maternity leave, family care, full-time student, government training scheme, unpaid worker and apprenticeship. These were then combined into a single variable called economically inactive which represented individuals that are not in employment or self-employment, similar to the methodology followed in Booker and Sacker (2012). Long-term sickness was retained as it was originally, due to the different implication of its labour market status and potential impact on mental health.

Independent Variables - Labour Market Status Transition Variables

Using the labour market status dummies already created, the labour market transition variables were created through recoding of the Job Status dummies for each wave starting from the second wave. A labour market transition represents the change in labour market status at the time of the interview from the previous period to the current period. All transitions were generated as dummy variables and all possible combinations of transitions were created. The descriptive statistics of labour market transition variables are shown below in Table 4 and frequencies are provided in Appendix A.1.2.

Table 4: **Descriptive Statistics of Labour Market Transition Variables**

Labour Market Transitions	**Male %**	**Female %**
1 Remains Employed	55.76	45.22
2 Remains Unemployed	2.41	1.05
3 Remains Long-term Sick	2.78	2.32
4 Remains Economically Inactive	7.06	16.80
5 Unemployed to Employed/Self Employed	1.76	0.98
6 Unemployed to Long Term Sick	0.36	0.23
7 Unemployed to Economically Inactive	0.51	0.86
8 Employed/Self Employed to Unemployed	1.41	0.84
9 Employed/Self Employed to Long Term Sick	0.28	0.26
10 Employed/Self Employed to Economically Inactive	1.22	3.08
11 Long Term Sick to Employed/Self Employed	0.16	0.14
12 Long Term Sick to Unemployed	0.28	0.18
13 Long Term Sick to Economically Inactive	0.38	0.51
14 Economically Inactive to Employed/Self Employed	1.55	3.66
15 Economically Inactive to Unemployed	0.67	0.94
16 Economically Inactive to Long Term Sick	0.29	0.46
Missing	23.14	22.47
Total	**100.0**	**100.0**

While generating labour market transition variables from the labour market status variables it should be noted that lag variables do not exist for the all years. This pertains to all readings of wave 1 and for the year preceding the first year of any individual observation. In these cases, the labour market transition variable is coded as a missing value.

In the final panel used, the number of missing values for labour market transitions are 89,443.

Independent Variables - Control Variables

The control variables selected for the research along with their descriptive statistics are described below. All control variables were re-coded for inapplicable, refusal to answer and don't know responses as missing values in the final panel.

General Physical Health: The self-reported general state of health variable as existed in the panel was recoded for the regression. The possible answers to this question across the BHPS and US datasets included Excellent, Very Good, Good, Fair, Poor and Very Poor. However, due to differences across the two datasets, Very Good and Good were recoded together as Good and Very Poor and Poor were also recoded together as Poor. The number of missing observations for the General Health variable in the panel were 95.

Natural Log of Household Income: Monthly - Per Capita: Total household income of the last month which is present in the panel was recoded for use in the regression model. The size of the household which is also present in the data was used to arrive at the per capita household income of the last month for the individual. The per capita household income was then logged to arrive at the final variable used for controlling for income in the regression model. In the case of reported household income being 0, the logged household income was also recoded to 0. The number of missing observations for both household income per capita and log of household income per capita in the panel was 926.

Education Level: Highest educational qualifications for each individual were recoded for use in the panel. The possible answers to this question included Degree, Other Higher Degree, A level, GCSE, Other Qualification and No Qualification. The number of missing observations for the education level variable in the panel was 4,069.

Marital Status: Present legal marital status was recoded into 4 categories overall. These were Single as one category, Married or Civil Partnership as the next category, Separated, Divorced, Separated from Civil Partner and Ex-civil Partnership as another category and Widowed or Surviving Civil Partner as the last category. The number of missing observations for the marital status variable in the panel was 618.

Age: The year of birth variable was recoded with year of interview to generate the Age variable. The cut off age for the regression was taken as 16 to 65 based on the labour market focus of the research. There were no missing values for age in the panel. Subsequently all individuals were categorised into age banded dummies (16-25, 26-35, 36-45, 46-55, 56-65) for use in the regression model.

Number of Children: The number of children in each household were recoded for use in the present research from the existing information in the dataset. The number of missing observations in the panel for number of children were 759.

The summary statistics for the control variables used are shown in Table 5 and Table 6 below and frequencies are provided in Appendix A.1.3.

Table 5: **Descriptive Statistics of Control Variables**

General Health Level	Male %	Female %
1 Excellent	23.54	20.56
2 Good	56.69	57.19
3 Fair	14.24	15.40
4 Poor	5.51	6.83
Missing	0.02	0.03
Total	**100.0**	**100.0**
Marital Status	**Male %**	**Female %**
1 Single	37.87	32.78
2 Married or Civil Partnership	52.56	51.55
3 Separated or Divorced	8.57	13.06
4 Widowed or Surviving Partner	0.84	2.45
Missing	0.16	0.16
Total	**100.0**	**100.0**
Highest Education Levels	**Male %**	**Female %**
1 Degree	20.72	19.86
2 Other Higher Degree	8.99	11.34
3 A Level	25.81	20.30
4 GCSE	23.31	25.39
5 Other Qualification	8.94	9.17
9 No Qualification	11.14	12.95
Missing	1.09	0.99
Total	**100.0**	**100.0**
Number of Children	**Male %**	**Female %**
0	61.99	56.57
1	16.96	19.76
2	14.66	16.34
3	4.76	5.41
4	1.08	1.29
5	0.24	0.30
6	0.08	0.09
7	0.03	0.03
8	0.01	0.01
9	0.00	0.00
10	0.00	0.00
Missing	0.18	0.20
Total	**100.0**	**100.0**

Table 6: **Summary Statistics for Control Variables**

Variable	N	Missing	Mean	SD	Min	Max
Household Income Per Capita: Last Month	391902	926	1229.39	1048.21	0	34359.98
Log Household Income Per Capita	391902	926	6.83	0.84	0	10.44
General Health Level	392733	95	2.05	0.78	1	4
Marital Status	392210	618	1.79	0.7	1	4
Highest Education Levels	388759	4069	3.65	2.35	1	9
AGE	392828	0	40.33	13.83	16	65
Number of Children	392069	759	0.72	1.03	0	10

2.3.4 Research Methodology

Linear regression models are useful to predict the relationship between independent variables and the dependent variable. Under appropriate statistical assumptions, a regression analysis is also helpful to investigate if there exists a causal relationship between the independent and dependent variables. A Fixed-Effects (FE) regression model is one that can provide unbiased estimates of causal inference within a panel data setting, if certain assumptions are valid. The present research uses a fixed-effects panel regression and we provide a brief summary below.

Fixed Effects Regression

A fixed-effects regression model explores the relationship between the independent and dependent variables within an entity and is useful for analysing the impact of variables that vary over time. In the case of this research, this is at the individual level and each individual has their own time-invariant characteristics that are affecting both the dependent variable and the independent variables.

The use of a fixed-effects model assumes that something within the individual (unobservable individual heterogeneity) may have an impact or cause a bias on the dependent variable, known also as the *between variation*. Under a panel data setting, by removing the impact of the time-invariant characteristics through a within transformation for deviations from the individual means, fixed-effects models allows us to control for time-constant unobserved individual heterogeneity. We are able to assess the net effect of the time-variant independent variables on the dependent variable, known as the *within variation*. The error term of the fixed-effects model is split into two components. The first component represents stable person-specific characteristics which are unobservable and related to the independent variables. The second component of the error term is the idiosyncratic error that varies across individuals and over time. The consistency of the fixed-effects estimates require the condition of strict exogeneity; that no correlation between the independent variables and the idiosyncratic error term exist for any of the lagged, present or future values between them. In addition, if an explanatory variable is time-invariant (such as gender) but necessary to be added into the model for the analysis, fixed-effects models are unsuitable.

Research Model Specifications

The current research involves two main fixed effects models with their detailed specifications elaborated below. For each of the two models used for the research, a slight variation in the specifications for each is also used and hence they are named as model 1A, 1B and model 2A, 2B. The explanatory variables differ slightly in each of the models used. Model 1A and 1B use labour market status as explanatory variables. While model 2A and 2B use labour market transitions as explanatory variables. However, all models use the same control variables and these include general health levels, marital status, education levels, per capita household income, number of children and age. Model 1A uses labour market status are originally defined in the US and BHPS datasets. Model 1B recodes the original labour market status into fewer categories of primary interest. Model 2A uses these recoded labour market status variables to generate labour market transition variables. Model 2B decomposes the labour market transitions into labour market status of the previous and present period for research purposes. Essentially, the regression models follow a logical extension for analysing the mental-health impacts from labour market status to transitions and a wide variation in results between models 1A and 1B would be a cause for concern.

Model 1A: The model tested the significance of all the labour market states as originally defined in the BHPS and US datasets. This gives us an idea of the mental-health levels associated with contemporaneous labour market status at any given point in time. The reference category for this model represented individuals who were employed. The various labour market states which represent the independent variables of interest in model 1A include self-employed, unemployed, retired, maternity leave, family care, full-time student, long term sickness, government training scheme, unpaid worker in family business and apprenticeship. Model 1A is specified as follows.

$$Y_{it} = \beta_1 X_{1it} + \beta_4 X_{4it} + \alpha_i + \mu_{it} \tag{1}$$

Where,

- Y_{it} is the dependent variable of total GHQ score of mental-health and i equals individual entity and t equals time.
- X_{1it} represents the Matrix of Contemporaneous Labour Market Status for individual i at time t, prior to combining of labour market states.
- X_{4it} represents the Matrix of Control Variables applied for individual i at time t.
- α_i denotes the individual-specific intercept for individual i, capturing time-invariant individual heterogeneity, with $i = 1....n$.
- μ_{it} is the idiosyncratic error term that varies across individuals over time.

Model 1B: The model tested the significance of labour market status on mental-health after re-coding the various labour market states in model 1A into the fewer categories used in the research. The independent variables therefore represent labour market status after combining employed and self-employed into a single category and after combining all other labour market states (not including long-term sick and unemployed) as economically inactive. Similar to model 1A, we estimate coefficients for each labour market status with mental health levels over the present time period. The reference category for this model represented individuals who were employed and self-employed. Long term sickness and unemployed are retained as originally defined in the data. All the remaining labour market states of retired, maternity leave, family care, full-time student, government training scheme, unpaid worker in family business and apprenticeship are combined into one single category and renamed as economically inactive. This provides a manageable framework to further evaluate labour market transitions as done in model 2A and 2B. The specification of Model 1B is as follows.

$$Y_{it} = \beta_2 X_{2it} + \beta_4 X_{4it} + \alpha_i + \mu_{it} \tag{2}$$

Where,

- Y_{it} is the dependent variable of total GHQ score of mental-health and i equals individual entity and t equals time.
- X_{2it} represents the Matrix of Labour Market Status for individual i at time t, subsequent to combining of the labour market states.
- X_{4it} represents the Matrix of Control Variables applied for individual i at time t.

- α_i denotes the individual-specific intercept for individual i, capturing time-invariant individual heterogeneity, with $i = 1....n$.
- μ_{it} is the idiosyncratic error term that varies across individuals over time.

Model 2A: The model tested the significance of the labour market transition variables on mental-health. We estimate the coefficients for the impact on mental-health associated with each of the labour market transitions. We retain the re-categorisation of labour market states as done in model 1B and employed and self-employed individuals are combined into a single category. The remaining labour market states of retired, maternity leave, family care, full-time student, government training scheme, unpaid worker in family business and apprenticeship are combined into one single category and renamed as economically inactive as done in model 1B. Subsequently, we generate transition variables between labour market states from one time period to the next. In essence, this model captures the impact of labour market interactions over two consecutive time periods on mental-health. The reference category for this model included individuals who remained in employment or self-employment over both time periods. Model 2A is specified as follows.

$$Y_{it} = \beta_5(X_{2it} - X_{2it-1}) + \beta_4 X_{4it} + \alpha_i + \mu_{it} \tag{3}$$

Where,

- Y_{it} is the dependent variable of total GHQ score of mental-health and i equals individual entity and t equals time.
- X_{2it} represents the Matrix of Labour Market Status for individual i at time t, subsequent to combining of the labour market states.
- X_{2it-1} represents the Matrix of Labour Market Status for individual i at time $t-1$, subsequent to combining of the labour market states.
- X_{4it} represents the Matrix of Control Variables applied for individual i at time t.
- α_i denotes the individual-specific intercept for individual i, capturing time-invariant individual heterogeneity, with $i = 1....n$.
- μ_{it} is the idiosyncratic error term that varies across individuals over time.

Model 2B: The reference category for this model is the same as in model 2A and included individuals who remained in employment or self-employment over two time periods. However, the model expresses a labour market transitions as the labour market status of the present and previous time period separately. We are now able to see the coefficients for the effects of labour market status in the previous and the present time periods separately on mental-health. Similar to model 2A, model 2B allows us to see the impact of labour market transitions over two time periods, but we are able to decompose the results to separately show the impact pertaining to the previous time period and for the current status. The coefficients in model 2B represent the generalised version of the results in model 2A and algebraically model 2A and 2B are the same. The specification of Model 2B is as follows.

$$Y_{it} = \beta_2 X_{2it} + \beta_3 X_{2it-1} + \beta_4 X_{4it} + \alpha_i + \mu_{it} \tag{4}$$

Where,

- Y_{it} is the dependent variable of total GHQ score of mental-health and i equals individual entity and t equals time.
- X_{2it} represents the Matrix of Labour Market Status for individual i at time t, subsequent to combining of the labour market states.
- X_{2it-1} represents the Matrix of Labour Market Status for individual i at time $t-1$, subsequent to combining of the labour market states.
- X_{4it} represents the Matrix of Control Variables applied for individual i at time t.
- α_i denotes the individual-specific intercept for individual i, capturing time-invariant individual heterogeneity, with $i = 1....n$.
- μ_{it} is the idiosyncratic error term that varies across individuals over time.

In all models, we control for a time trend by including year dummies. As a robustness check to our estimates from the above models, we compare results for similarly specified models using a random-effects and OLS estimator. In addition, we also compare the results between sub-samples of men and women and test to see if there are significant differences between both cohorts.

We also note that due to GHQ scores being inverse, a positive coefficient means a lower mental-health score overall. Similarly, a negative coefficient signifies an improvement in mental-health scores in this research. In order to test if the above fixed-effects models are suitable for the present research, we also conduct two statistical tests as described next.

Hausman Specification Test

Fixed-effects models allow for correlation between the α_i and the X_{it} terms. In the case that there exists no correlation between α_i and the X_{it} terms, the fixed-effects estimates will be inefficient and random-effects models will be better suited for the analysis.

The Hausman specification test is one such check that enables us to test this and was conducted to check the appropriateness of using fixed-effects in this research. The full Hausman specification test results are produced in Appendix A.1.4. The test returns a large and significant Hausman statistic with a p values less than 0.05 across all models. Therefore, in this case we reject the random-effects model in favour of the fixed-effects model.

Levene's Test for Equality of Variances - Heteroscedasticity

Heteroscedasticity is often referred to as *the problem of varying variance* and can result in the regression results being unreliable by way of the estimated standard errors being biased. The error term or residual of the regression model is assumed to be homoscedastic across all values of the predicted value of the dependent variable. This assumes that the variance of the residuals should not increase with fitted values of the dependent variable.

In the present research, the regressions were first run with the fixed-effects model and the presence of heteroscedasticity was tested between the dependent variable of mental-health and all the independent variables through the Levene's Test of Heteroscedasticity. A test result with a p value of less that 0.05 indicates that heteroscedasticity exists between the dependent and independent variables.

The results of the test showed that in the case of all independent variables, except for two of the labour market transition variables (unemployed to employed/self-employed and economically inactive to employed/self-employed), the p values returned were less than 0.05. This indicated the presence of heteroscedasticity and the results of the test are produced in Appendix A.1.5. In order to address this issue, we use robust standard errors in the regression models to correct for heteroscedasticity. This is expected to increase the statistical reliability of the results presented in the next section.

2.4 Results and Discussion

The fixed-effects regression model was run for each model to assess the impact of labour market status and transitions on mental-health. For the regression models, the base category was defined as employed in model 1A, employed or self-employed in model 1B, and remaining employed or self-employed in model 2A and 2B. Positive coefficients imply a worse off level of mental-health while negative coefficients demonstrate an improved level of well-being. The results for each model are discussed below.

2.4.1 Results - Model 1A

Model 1A had a base category of employed individuals and included a total of 387,242 observations. Model 1A incorporates the contemporaneous labour market status for individuals as defined in the BHPS and US survey. This allows us to get an idea of the mental-health scores associated with the various labour market states with respect to employed individuals.

Within the labour market status variables, the estimated coefficients for long-term sick and unemployed individuals are the highest at 2.08 and 1.67 signifying worse mental-health levels with significance levels at 1%. Being in family care also results in worse mental-health levels of 0.62 at 1% level of significance. The effect sizes seen here signify lower levels of mental-health that can be interpreted as a similar deterioration of mental-health for individuals who are widowed relative to those that are single. Widowed or surviving partners have a higher GHQ score of 1.54 at the 1% level of significance. Thus, we see the lower level of well-being for unemployed individuals (relative to an employed individual) is marginally higher to the lower level of well-being seen in a widowed individual (relative to a person who is single). The labour market status of retired individuals shows an improvement in mental-health levels of -0.27 at 1% level of significance with respect to employed individuals.

Controlling for general health levels shows estimated coefficients of 4.80, 2.19 and 0.74 for health levels of poor, fair and good. We note that general health is a significant control for mental wellbeing and all of the estimated coefficients are with respect to individuals with excellent reported health.

The natural log of household income per capita returns a negative coefficient of -0.12 implying an improvement in mental health-levels as income increases. For marital status with respect to the baseline category of being single, a deterioration of mental-health was seen in individuals who are separated or divorced with a coefficient of 0.26. All of the results are significant at 1%, but we note that effect sizes are considerably smaller than the estimated effect of being unemployed.

The number of children variable showed improvements in mental-health associated with increases in number of children. The estimated coefficient was -0.04 with significance at 5% levels. With respect to highest education level attained, none of results were significant. The full results for model 1A are shown below in Table 7.

Table 7: **Fixed Effects Results - Model 1A**

VARIABLES	FE-Model 1A
Self Employed	-0.0380
	(0.0501)
Unemployed	1.676***
	(0.0567)
Retired	-0.273***
	(0.0613)
Maternity Leave	-0.0425
	(0.0990)
Family Care	0.629***
	(0.0560)
Full Time Student	-0.0120
	(0.0582)
Long Term Sickness	2.081***
	(0.0978)
Government Training Scheme	-0.0821
	(0.212)
Unpaid Worker in Family Business	0.155
	(0.527)
Apprenticeship	-0.112
	(0.336)
General Health Level = 2, Good	0.748***
	(0.0228)
General Health Level = 3, Fair	2.192***
	(0.0379)
General Health Level = 4, Poor	4.808***
	(0.0703)
Marital Status = 2, Married or Civil Partnership	0.0431
	(0.0566)
Marital Status = 3, Separated or Divorced	0.267***
	(0.0839)
Marital Status = 4, Widowed or Surviving Partner	1.540***
	(0.184)
Highest Education Levels = 2, Other Higher Degree	0.0142
	(0.123)
Highest Education Levels = 3, A Level	-0.0750
	(0.0892)
Highest Education Levels = 4, GCSE	-0.0724
	(0.103)
Highest Education Levels = 5, Other Qualification	-0.0330
	(0.151)
Highest Education Levels = 9, No Qualification	-0.209
	(0.143)
Log Household Income Per Capita	-0.126***
	(0.0173)
Number of Children	-0.0432**
	(0.0199)
Age Bands = 2, Aged: 26-35	0.292***
	(0.0564)
Age Bands = 3, Aged: 36-45	0.399***
	(0.0793)
Age Bands = 4, Aged: 46-55	0.250**
	(0.0980)
Age Bands = 5, Aged: 56-65	-0.238**
	(0.117)
Constant	22.48***
	(0.182)
Observations	387,242
Number of Individuals	86,651
R-squared	0.050
Year Dummies	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

2.4.2 Results - Model 1B

Model 1B combined the contemporaneous labour market status into a single category for employed and self-employed and this was used as the reference category for the regression model. The status for unemployed and long-term sick individuals are retained as it originally were in model 1A. The categories of retired, family care, full-time student, government training scheme, unpaid worker in family business, apprenticeship and maternity leave were also combined into a single category and recoded as economically inactive. The categorisation of labour market status in model 1B is a step towards the specification of model 2 where we investigate labour market transitions. We expect to see differences in the estimates and significance levels between model 1A and model 1B as the reference category for both models are different. Similar to model 1A, the number of observations in model 1B are 387,242.

We see the estimated coefficient for labour market status for long-term sick individuals are the highest at 2.10, unemployed individuals have a coefficient of 1.64 and economically inactive persons have a smaller coefficient of 0.14. The results have a level of significance of 1% and the positive sign for all the estimated coefficients signify a deterioration in mental-health with respect to the base category of individuals who are in either employment or self-employment. We can interpret this deterioration in mental-health for the unemployed relative to their employed or self-employed peers as slightly larger in magnitude to the fall in mental-health seen for a widowed individual relative to an individual with a marital status of being single.

The estimated coefficient of being widowed or a surviving partner had a coefficient of 1.49 while being separated or divorced had a coefficient of 0.28, with respect to being single. Both these results were significant at 1% levels and implied worse off levels of mental health.

Controlling for general health levels, with respect to the base category of individuals in excellent reported health, those in poor, fair and good health had estimated coefficients of 4.80, 2.19 and 0.75 respectively. All the results for general health were significant at a level of 1% with notable effect sizes estimated.

The natural log of household income returned a negative coefficient of - 0.12 at a 1% level of significance, implying improvements in mental well-being over higher levels of income. Though the effect sizes are small in magnitude when compared to the fall in mental-health levels seen with being unemployed.

Controlling for highest education level attained showed that with respect to those having a degree, individuals who had no qualification had improved levels of mental health with a coefficient of -0.37 at 1% levels of significance. Those with just a GCSE qualification enjoyed better mental-health with a coefficient of -0.21 and those with just A level qualification had a coefficient of -0.17, both at 5% level of significance. The significant results for education levels seen in model 1B are noted, as these were previously insignificant estimates in model 1A.

Similarly, the variable for number of children while retaining a positive impact on mental-health, as seen in model 1A, was no longer significant. We note that the categorisation of the various labour market status has impacted some of the levels of significance in model 1B. The full results of model 1B are shown in Table 8 below.

Table 8: **Fixed Effects Results - Model 1B**

VARIABLES	FE-Model 1B
Labour Market Status = 2, Unemployed	1.645***
	(0.0562)
Labour Market Status = 3, Long-term Sickness	2.104***
	(0.0964)
Labour Market Status = 4, Economically Inactive	0.144***
	(0.0356)
General Health Level = 2, Good	0.750***
	(0.0228)
General Health Level = 3, Fair	2.195***
	(0.0379)
General Health Level = 4, Poor	4.807***
	(0.0702)
Marital Status = 2, Married or Civil Partnership	0.0694
	(0.0566)
Marital Status = 3, Separated or Divorced	0.286***
	(0.0839)
Marital Status = 4, Widowed or Surviving Partner	1.497***
	(0.184)
Highest Education Levels = 2, Other Higher Degree	-0.0529
	(0.122)
Highest Education Levels = 3, A Level	-0.178**
	(0.0863)
Highest Education Levels = 4, GCSE	-0.215**
	(0.0987)
Highest Education Levels = 5, Other Qualification	-0.171
	(0.148)
Highest Education Levels = 9, No Qualification	-0.370***
	(0.139)
Log Household Income Per Capita	-0.122***
	(0.0173)
Number of Children	-0.0320
	(0.0199)
Age Bands = 2, Aged: 26-35	0.325***
	(0.0564)
Age Bands = 3, Aged: 36-45	0.443***
	(0.0792)
Age Bands = 4, Aged: 46-55	0.315***
	(0.0978)
Age Bands = 5, Aged: 56-65	-0.206*
	(0.117)
Constant	22.51***
	(0.180)
Observations	387,242
Number of Individuals	86,651
R-squared	0.050
Year Dummies	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.4.3 Results - Model 2

The results of model 2A and 2B are shown below in Table 9 and discussed subsequently.

Table 9: **Fixed Effects Results - Model 2A and 2B**

VARIABLES	FE-Model 2B	FE-Model 2A
Labour Market Status = 2, Unemployed	0.751***	
	(0.114)	
Labour Market Status = 3, Long-term Sickness	1.336***	
	(0.189)	
Labour Market Status = 4, Economically Inactive	0.225	
	(0.163)	
Labour Market Transitions = 2, Remains Unemployed	0.514***	1.265***
	(0.140)	(0.110)
Labour Market Transitions = 3, Remains Long-term Sick	0.169	1.505***
	(0.183)	(0.150)
Labour Market Transitions = 4, Remains Economically Inactive	-0.321**	-0.0961*
	(0.158)	(0.0529)
Labour Market Transitions = 5, Unemployed to Employed/Self Employed	-0.626***	-0.626***
	(0.0773)	(0.0773)
Labour Market Transitions = 6, Unemployed to Long Term Sick	0.998***	2.334***
	(0.263)	(0.222)
Labour Market Transitions = 7, Unemployed to Economically Inactive	-0.221	0.00413
	(0.187)	(0.113)
Labour Market Transitions = 8, Employed/Self Employed to Unemployed	1.315***	2.066***
	(0.144)	(0.101)
Labour Market Transitions = 9, Employed/Self Employed to Long Term Sick	2.183***	3.518***
	(0.277)	(0.226)
Labour Market Transitions = 10, Employed/Self Employed to Economically Inactive	-0.514***	-0.289***
	(0.167)	(0.0593)
Labour Market Transitions = 11, Long Term Sick to Employed/Self Employed	-1.429***	-1.429***
	(0.270)	(0.270)
Labour Market Transitions = 12, Long Term Sick to Unemployed	0.614**	1.365***
	(0.243)	(0.226)
Labour Market Transitions = 14, Economically Inactive to Employed/Self Employed	-0.499***	-0.499***
	(0.0526)	(0.0526)
General Health Level = 2, Good	0.763***	0.763***
	(0.0260)	(0.0260)
General Health Level = 3, Fair	2.229***	2.229***
	(0.0427)	(0.0427)
General Health Level = 4, Poor	4.831***	4.831***
	(0.0789)	(0.0789)
Marital Status = 2, Married or Civil Partnership	0.0327	0.0327
	(0.0658)	(0.0658)
Marital Status = 3, Separated or Divorced	0.204**	0.204**
	(0.0959)	(0.0959)
Marital Status = 4, Widowed or Surviving Partner	1.503***	1.503***
	(0.208)	(0.208)
Highest Education Levels = 2, Other Higher Degree	-0.0137	-0.0137
	(0.151)	(0.151)
Highest Education Levels = 3, A Level	-0.219**	-0.219**
	(0.102)	(0.102)
Highest Education Levels = 4, GCSE	-0.130	-0.130
	(0.122)	(0.122)
Highest Education Levels = 5, Other Qualification	0.0706	0.0706
	(0.193)	(0.193)
Highest Education Levels = 9, No Qualification	-0.0499	-0.0499
	(0.198)	(0.198)
Log Household Income Per Capita	-0.124***	-0.124***
	(0.0206)	(0.0206)
Number of Children	-0.00652	-0.00652
	(0.0234)	(0.0234)
Age Bands = 2, Aged: 26-35	0.321***	0.321***
	(0.0661)	(0.0661)
Age Bands = 3, Aged: 36-45	0.451***	0.451***
	(0.0915)	(0.0915)
Age Bands = 4, Aged: 46-55	0.369***	0.369***
	(0.112)	(0.112)
Age Bands = 5, Aged: 56-65	-0.0715	-0.0715
	(0.133)	(0.133)
Labour Market Transitions = 13, Long Term Sick to Economically Inactive		0.225
		(0.163)
Labour Market Transitions = 15, Economically Inactive to Unemployed		0.751***
		(0.114)
Labour Market Transitions = 16, Economically Inactive to Long Term Sick		1.336***
		(0.189)
Constant	22.52***	22.52***
	(0.208)	(0.208)
Observations	300,357	300,357
R-squared	0.053	0.053
Number of Individuals	67,201	67,201
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of model 2A and 2B are discussed together. In model 2A and 2B, the reference category specified are individuals who have remained in employment or self-employment for the current time period a well as the previous time period. The number of observations reduce to 300,357 in model 2 due to the incorporation of lag variables. Model 2A incorporates the labour market transition variables as predictors of mental-health. This allows us to check the mental-health levels associated with a transition into and out of each labour market state. Model 2A and 2B are equivalent but differently parameterised. In model 2B we disentangle the effects of a labour market transition on mental-health to separately view the impact of the effect for the current time period and the previous time period. Inclusion of labour market status as explanatory variables in model 2B requires that three of the possible transitions are omitted to avoid multicollinearity.

As in the previous section we interpret the magnitude of effect sizes seen on mental-health stemming from labour market transitions as relative to those seen in the case of widowed individuals who were found to have a GHQ score of 1.503 higher than individuals with a marital status of being single.

The results of model 2A shows that individuals who remained in long-term sickness and those that remained unemployed over both periods had worse of levels of mental health with estimated coefficients of 1.50 and 1.26 respectively, both at 1% level of significance. The estimated coefficient for individuals that remained economically inactive is -0.0961 at 10% level of significance. In model 2B we disentangle the effects of remaining in long-term sickness across both time-periods and see that for individuals who remain in long-term sickness, the effect of the current period is estimated at 1.33 with levels of significance at 1% and that of the lag period at 0.169. Notably, the result for the lag is not significant, implying a loss of predictive power for long-term sickness beyond the current year for those that are already in long-term sickness. In the case of individuals who remain in unemployment for two periods, the effect of the present period is 0.75 and in the previous period 0.51, both with levels of significance at 1%, indicating the longer term negative impacts of unemployment on mental-health.

The estimated coefficients of the transition variables show an interesting picture. The movement from an employed or self-employed status into unemployment is associated with lower mental health levels, with an effect size of 2.06 at 1% level of significance. This labour market transition when split up, shows a coefficient of 1.31 for the lag period and 0.75 for the present status, both at 1% level of significance. The higher effect size in the lag period implies that the event of losing employment has a higher detrimental effect on mental-health than that of the present status when unemployed. For the reverse transition of unemployed into employed/self-employed the estimated coefficient is -0.62 at 1% level of significance, which indicates the asymmetry of impacts on mental-health.

The movement from an employed or self-employed status into long-term sickness had an effect sizes of 3.51 at 1% level of significance. While this signified lower mental health for long-term sick individuals, the effect for the lag period showed a coefficient of 2.18 and for the present status of 1.33, both at 1% level of significance. As seen previously, higher effect size in the lag period implies that the effect of moving out of employment has a higher detrimental effect on mental-health than that of the present status of being long-term sick. In the case of the reverse transition from long-term sickness into employed/self-employed, a beneficial impact on mental-health was seen with an estimated coefficient of -1.42 at 1% level of significance. Once again we identify asymmetry in the impacts.

The movement from unemployed to long-term sickness is associated with lower levels of mental-health at 1% level of significance with an overall coefficient of 2.33. This decomposes to the lag effect of 0.99 and present status effect of 1.33, both at 1% levels. The reverse transition from long-term sickness into unemployment has a coefficient of 1.36 at 1% level of significance. This was seen to be 0.75 at 1% levels in the present period and 0.61 for the lag period at 5% levels.

Moving from economically inactive into employment/self-employment leads to improved levels of mental-health with a coefficient of -0.49. The reverse transition of moving from employment/self-employment into economically inactive is also associated with improved levels of mental health, but with a smaller coefficient of -0.28. Both results hold at a 1% level of significance. Moving from economically inactive into long-term sickness and unemployment are associated with lower levels of mental health at 1% levels of significance, though the former has an effect size of 1.33, while the latter has an effect size of 0.75. However, due to the nature of the variable economically inactive being a combination of various contemporaneous labour market states, care must be taken while making conclusions based on this result.

The estimated coefficients for all control variables in model 2A and 2B are, by definition equivalent. As seen in model 1A and 1B, the natural log of household income is seen to be significant at 1% with an estimated coefficient of -0.12. Once again, implying a positive association better mental-health with higher incomes.

The controls for general health levels also returned a similar result as found in model 1A and 1B, with respect to the base category of individuals with excellent reported health. At 1% level of significance, individuals in poor, fair and good health were found to have estimated coefficients of 4.83, 2.22 and 0.76 respectively.

Controlling for marital status, with respect to individuals who are single, showed an almost similar result to model 1A and 1B. Widowed or surviving partners had a coefficient of 1.50 significant at the 1% level. Separated or divorced individuals had a coefficient of 0.20, but with significance now at the 5% level.

For highest educations level attained, only the result for A levels was significant at 5% levels with a coefficient of -0.21, implying a slightly better level of mental-health when compared to those with a degree. Similar to model 1B, the control variable for number of children in model 2 had a positive impact on mental-health, but was insignificant.

2.4.4 Overall Interpretation of the Results

Comparing models 1 and 2, we see that unemployed individuals showed consistency by being in worse mental health compared to their employed peers and maintained a level of significance of 1%. However, the effect sizes estimated were higher in Model 1 when only contemporaneous labour market status was considered. The inclusion of the lag variables of labour market status implied a reduced impact on mental-health in the current period. This implies the existence of anticipation effects as also discussed in Frijters et al. (2011).

Long-term sickness leading to lower levels of mental-health was significant across all models at 1% levels of significance. The effect size was again seen to be higher in model 1 which did not incorporate the effects from the previous time period.

The estimated coefficients for control variables showed strong consistency in all models in the case of general health, income and marital status of widowed with similar effect sizes and 1% levels of significance.

The main contribution of this research has been to reinforce our understanding of the relationship between mental-health and labour market transitions and how these impacts compare relative to other significant life events such as loss of a partner or entry into long term sickness. Further, the use of a 25 year dataset allows for the analysis to be conducted over a much longer period than what is commonly found in the existing literature.

Presence of Adaptation: Notably, a comparison of a transition from employed/self-employed into unemployment with individuals remaining unemployed over both periods show evidence of adaptation over two time periods. Those remaining unemployed over both periods are seen to have a lower deterioration of on their mental-health with an estimated coefficient of 1.26, while individuals transitioning from employment/self-employment into unemployment had an estimated coefficient of 2.06. Both results hold at 1% level of significance. The results are aligned to the previous findings of Frijters et al. (2011) and Clark and Georgellis (2013) but in the case of the present research, we limit the analysis to the change in mental-health over two periods. Clark and Georgellis (2013) though has evaluated the change in wellbeing over a much longer time period following job loss and similar to their findings, the recovery of mental-health following job loss is not complete.

A similar result is seen when comparing the estimated coefficients of individuals transitioning from employed/self-employed into long-term sick (3.51) with those that remain in long-term sickness (1.50), with 1% level of significance in both cases.

These results indicate that in the immediate period following entry into unemployment or long term sickness, individuals are likely to suffer a large fall in wellbeing as a result of the immediate momentary shock. These effects moderate (though not fully) over the next time period. Hence, we see evidence that the mental-health effects of labour market transitions show signs of partial adaptation and this result follows closely with the findings of Clark and Oswald (1994).

Asymmetric Impacts: In the case of reverse transitions, we see that the negative impacts of moving from employment/self-employment into unemployment are higher than the improvements seen in the reverse transition (2.06 vs -0.62 respectively), with level of significance at 1% both ways. This asymmetry in mental-health follows closely with the results in Frijters et al. (2011). Similar to the published literature in Baumeister et al. (2001) we see signs of a "negativity bias" that overweight bad outcomes more than good outcomes.

Similarly, for transitions between long-term sickness and employment/self-employment, the negative effects of becoming long-term sick are higher than the positive effects seen in the reverse transition (3.51 vs -1.42 respectively), again with a 1% level of significance for both directions of the transition. Overall, these results indicate that mental-health has a higher vulnerability to negative impacts than positive impacts.

The rationale for such a result, wherein subjective wellbeing are much more sensitive to negative impacts as compared to positive impacts can be explained in terms of Prospect Theory. First proposed by Kahneman (1979), Prospect Theory provides a practical framework to interpret these results. Prospect theory encompasses four distinct elements under which individuals evaluate risk. These include Reference Dependence (individuals measure gains and losses relative to some reference point), Loss Aversion (individuals are more sensitive to losses over gains of the same magnitude), Diminishing Sensitivity (individuals are risk averse over gains and risk seeking over losses), and Probability Weighting (individuals overweight low probability outcomes and underweight high probability outcomes). Particularly in the case of the present research, we see that the dominating effect is the element of loss aversion as defined by prospect theory. Individuals are more sensitive to losses over gains and therefore face larger drops in their mental-health stemming from a transition into unemployment as compared to the smaller increase in mental-health for the reverse transition into employment.

2.4.5 Robustness Checks

The robustness checks for the present research included comparing the results of the Fixed Effects (FE) with Pooled Ordinary Least Squares (OLS) estimators. Overall, the results showed consistency in terms of the sign and magnitude of the estimated coefficients between the FE, OLS models. The results of the robustness checks done are explained briefly below and produced in Appendix A.1.6.

Model 1A - Robustness Checks - Fixed Effects & OLS

Overall the estimated coefficients are larger in the case of OLS regression when compared to FE. The level of significance has also increased in some of the variables. The effect sizes of long-term sick individuals have larger point estimates in the OLS model. For unemployed individuals the estimated effects were lower in OLS in comparison with FE. For individuals in family care, the estimated effect sizes were higher in OLS. In the case of self-employed individuals who showed an insignificant improvement in mental-health in FE, the results while directionally similar in OLS are now significant at 1%. Similarly, in the case of apprenticeship which was associated with an improvement in mental-health, but not significant for FE, we find similar results for OLS which are now significant at 1%. While FE showed a non-significant result of improved mental-health for students, the OLS results showed lower mental-health for students which was significant at 1%.

Control variables also showed an increase in effect sizes in the case of general health with larger point estimates in OLS when compared to FE. Marital status of being married which was not significant in FE showed improved level of mental-health in the case of OLS and was significant at 1% levels. For OLS, education levels had 1% level of significance showing improved levels of mental-health for lower levels of education, except in the case of having other degree. Income had a similar result across FE and OLS with estimated effect sizes slightly higher in OLS.

Model 1B - Robustness Checks - Fixed Effects & OLS

The results of the FE estimates in Model 1B show a similar trend with larger point estimates for most variables under OLS. Unemployed individuals had a similar result with slightly higher estimated coefficients in OLS. Long-term sickness and economically inactive individuals also had a higher estimated effects in OLS and the significance levels remained the same at 1%, compared to FE.

The control variables of general health showed an increase in estimated coefficients as health deteriorated and the increase was notably higher for OLS. Married individuals had a positive result of improved mental-health in OLS which was significant at 1%. This result was however insignificant in the FE model.

While education levels were not significant in FE, they showed significant results of improved mental-health associated with lower levels of education for all categories except having another higher degree in OLS. The results for income was again similar with slightly higher estimated effects in OLS.

Model 2A & 2B - Robustness Checks - Fixed Effects & OLS

Model 2A and 2B being equivalent in design are discussed together. Labour market status of unemployed and long-term sickness are associated with lower levels of mental-health for the current period in FE and OLS, but with higher estimated coefficients in the OLS model. However, the OLS result for the lag period of unemployed individuals returned an insignificant result, while it was found to be significant at 1% in FE.

In long-term sick individuals, the current period estimates were significant at 1% in FE and OLS, but with higher effect sizes in OLS compared to FE. The results of the lag period were insignificant in both FE and OLS models, but directionally opposite.

Economically inactive which was insignificant in FE, was found to be significant at 1% levels with a negative impact on mental health in the case of the current period for OLS. In the lag period, it was also seen to be indicative of improved mental-health with higher estimated coefficients in OLS at 1% level of significance, but only had a 5% level of significance in FE.

The remaining labour market transitions overall had a consistent result with similar to higher point estimates for OLS when compared to FE in the transitions associated with lower levels of mental-health. For the transitions associated with improved mental-health, OLS saw lower estimated coefficients compared to FE.

The control variables for general health had much higher effect sizes in OLS with significance at 1% levels. Income effects were consistent across FE and OLS models, but slightly higher in OLS. A married individual was found to be in improved mental health only in OLS at 1% level of significance. Effect sizes for divorced or separated individuals were higher in OLS as compared to FE, with 1% and 5% level of significance respectively. For widowed individuals the estimated effect was significant at 1% in both models, but the effect sizes were smaller in OLS compared to FE. Highest education level attained, which were indicative of improved mental-health with lower qualifications, showed the majority of significant results in the case of OLS, except for those with other higher degree. However, in the case of FE only those with A levels showed significant results at 5%.

2.4.6 Fixed Effects - Gender Based Sub-Samples

The fixed-effects regressions for male and female sub-samples are discussed below with tests for significant differences between both genders.

Model 1A - Fixed Effects for Men vs Women

The impact of unemployment and long-term sickness, while significant at 1% for both men and women, is found to have higher effect sizes in both labour market states for men. Family care, with levels of significance at 1% for both sub-samples are also seen to be associated with lower mental-health levels in the case of men. In case of retirement, the improvement in mental-health is found to be higher for women at 1% level of significance, but the result for men are significant at 5%.

Control variables of general health are found to have higher coefficients for women in all categories. Income is seen to have a stronger effect of improving mental-health for women than men with the level of significance at 1% for both men and women. Marital status of separation is found to impact men with a higher estimated coefficient and at 1% level of significance and for women the effect size is lower with a level of significance of 10%. In the case of widowed individuals, the impact is higher for women with both sub-samples having a level of significance of 1%. Education levels attained are insignificant for both men and women, except for the case of men with no qualification, who have improved mental health scores with a significance of 5%. Lastly, the number of children variable are seen to be associated with improved mental-health for men at 5% level of significance but the result is insignificant for women. The full results are presented below in Table 10.

Table 10: **Model 1A - Fixed Effects for Men & Women Sub-Samples**

VARIABLES	FE-Men-Model 1A	FE-Women-Model 1A
Self Employed	0.0203	-0.112
	(0.0624)	(0.0830)
Unemployed	1.814***	1.549***
	(0.0775)	(0.0836)
Retired	-0.231**	-0.305***
	(0.0916)	(0.0817)
Maternity Leave	-3.520***	-0.0347
	(1.332)	(0.0995)
Family Care	0.831***	0.577***
	(0.192)	(0.0601)
Full Time Student	-0.0362	0.0102
	(0.0828)	(0.0808)
Long Term Sickness	2.278***	1.951***
	(0.143)	(0.134)
Government Training Scheme	0.121	-0.287
	(0.249)	(0.356)
Unpaid Worker in Family Business	2.075	-0.427
	(1.399)	(0.532)
Apprenticeship	0.131	-0.438
	(0.368)	(0.603)
General Health Level = 2, Good	0.605***	0.872***
	(0.0313)	(0.0327)
General Health Level = 3, Fair	1.819***	2.488***
	(0.0525)	(0.0536)
General Health Level = 4, Poor	4.373***	5.130***
	(0.108)	(0.0926)
Marital Status = 2, Married or Civil Partnership	0.120	-0.0183
	(0.0745)	(0.0830)
Marital Status = 3, Separated or Divorced	0.350***	0.204*
	(0.118)	(0.117)
Marital Status = 4, Widowed or Surviving Partner	1.102***	1.654***
	(0.308)	(0.227)
Highest Education Levels = 2, Other Higher Degree	0.190	-0.0938
	(0.186)	(0.162)
Highest Education Levels = 3, A Level	2.77e-05	-0.137
	(0.127)	(0.124)
Highest Education Levels = 4, GCSE	-0.151	-0.0202
	(0.146)	(0.143)
Highest Education Levels = 5, Other Qualification	-0.0715	-0.00448
	(0.209)	(0.215)
Highest Education Levels = 9, No Qualification	-0.409**	-0.0409
	(0.198)	(0.202)
Log Household Income Per Capita	-0.115***	-0.133***
	(0.0241)	(0.0250)
Number of Children	-0.0643**	-0.0205
	(0.0275)	(0.0285)
Age Bands = 2, Aged: 26-35	0.459***	0.150*
	(0.0784)	(0.0801)
Age Bands = 3, Aged: 36-45	0.651***	0.198*
	(0.111)	(0.112)
Age Bands = 4, Aged: 46-55	0.433***	0.109
	(0.137)	(0.138)
Age Bands = 5, Aged: 56-65	-0.0845	-0.350**
	(0.164)	(0.166)
Constant	21.93***	22.90***
	(0.248)	(0.263)
Observations	173,885	213,358
R-squared	0.049	0.052
Number of Individuals	40,034	46,650
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Test for Significant Differences between Men and Women

We also check if the point estimates for men and women have statistically significant differences to each other. Using a pooled regression specification, we simultaneously estimate the effects for men and women and test to see if the differences between estimates are significant. The results, shown as p-values for the test, are shown below in Table 11.

Table 11: **Test for Significant Differences between Genders - Model 1A**

Variable	**Prob >chi2**	**Significant Differences**
SELF-EMPLOYED	0.002	**1%**
UNEMPLOYED	0.125	No
RETIRED	0.020	**5%**
MATERNITY_LEAVE	0.002	**1%**
FAMILY_CARE	0.000	**1%**
FULLTIME_STUDENT	0.342	No
LONGTERM_SICK	0.045	**5%**
GOVT_TRAINING_SCHEME	0.227	No
UNPAID_WORKER	0.085	**10%**
APPRENTICESHIP	0.498	No

Overall we note that unemployed men and women do not have significantly different outcomes with respect to their impact on mental-health. We see that women in self-employment, family care and maternity have significant differences to men at the 1% level of significance. We also see significant differences between genders in the case of retired, long-term sick, and unpaid workers at 5%, 5% and 10% levels of significance respectively.

Model 1B - Fixed Effects for Men vs Women

In model 1B, the impact of unemployment and long-term sickness are found to have higher effect sizes in men over women, both with levels of significance at 1%. Economically inactive status, representing not in direct employment or self-employment, has an insignificant result for men, but is indicative of lower levels of mental-health for women at 1% level of significance.

The impact of general health is seen to be more pronounced for women than men with the level of significance for both men and women are at 1%. Income plays a stronger role for women in improving mental health over men and the results are significant at 1% for both. For marital status, a married man showed an improvement in mental-health at 10% level of significance but the result was insignificant for women. Being separated had a higher effect size for men and with a 1% level of significance, while women had a lower effect size and at the 5% level of significance. A widowed woman is found to be in worse off mental-health compared to their male counterpart, but both genders have a 1% level of significance.

In the case of highest educational level attained, women have a slightly improved mental-health score in the case of A levels, which is significant at 5% while this result is not significant for men. In the case of no educational qualifications, men are seen to enjoy improved mental-health at 5% level of significance but the result is insignificant for women. Similar to model 1A, the number of children variable are seen to be associated with improved mental-health for men at 5% level of significance but the result is insignificant for women. The full results are presented below in Table 12.

Table 12: **Model 1B - Fixed Effects for Men & Women Sub-Samples**

VARIABLES	FE-Men-Model 1B	FE-Women-Model 1B
Labour Market Status = 2, Unemployed	1.781***	1.499***
	(0.0765)	(0.0831)
Labour Market Status = 3, Long-term Sickness	2.291***	1.963***
	(0.141)	(0.132)
Labour Market Status = 4, Economically Inactive	-0.0458	0.200***
	(0.0603)	(0.0438)
General Health Level = 2, Good	0.606***	0.874***
	(0.0313)	(0.0327)
General Health Level = 3, Fair	1.819***	2.494***
	(0.0525)	(0.0536)
General Health Level = 4, Poor	4.368***	5.133***
	(0.108)	(0.0926)
Marital Status = 2, Married or Civil Partnership	0.126*	0.0177
	(0.0745)	(0.0829)
Marital Status = 3, Separated or Divorced	0.360***	0.230**
	(0.118)	(0.117)
Marital Status = 4, Widowed or Surviving Partner	1.078***	1.616***
	(0.308)	(0.226)
Highest Education Levels = 2, Other Higher Degree	0.190	-0.177
	(0.186)	(0.161)
Highest Education Levels = 3, A Level	-0.00413	-0.267**
	(0.124)	(0.119)
Highest Education Levels = 4, GCSE	-0.157	-0.197
	(0.142)	(0.136)
Highest Education Levels = 5, Other Qualification	-0.0791	-0.175
	(0.205)	(0.211)
Highest Education Levels = 9, No Qualification	-0.424**	-0.242
	(0.193)	(0.196)
Log Household Income Per Capita	-0.115***	-0.131***
	(0.0240)	(0.0249)
Number of Children	-0.0616**	-0.00667
	(0.0275)	(0.0284)
Age Bands = 2, Aged: 26-35	0.469***	0.193**
	(0.0784)	(0.0801)
Age Bands = 3, Aged: 36-45	0.673***	0.260**
	(0.111)	(0.112)
Age Bands = 4, Aged: 46-55	0.465***	0.202
	(0.137)	(0.138)
Age Bands = 5, Aged: 56-65	-0.0626	-0.301*
	(0.163)	(0.165)
Constant	21.92***	22.94***
	(0.245)	(0.260)
Observations	173,885	213,358
R-squared	0.049	0.051
Number of Individuals	40,034	46,650
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Model 2A & 2B - Fixed Effects for Men vs Women

As shown earlier, model 2A and 2B are equivalent and so discussed jointly. The analysis pertains to two consecutive time periods and in the case of unemployment, the impact on men is seen to have a higher effect size than on women on both the current period and lag period, with significance levels of 1% in both men and women.

In the case of long-term sickness, while the results are significant at 1% for men and women, men are seen to be more vulnerable to with higher estimated coefficients for both periods combined, but the impact for women is found to be higher in the present period and insignificant in the previous period.

For economically inactive status, the results for women are insignificant in both periods. Men however, experience a positive impact on mental-health from economic inactivity in the previous period with significance at 1% and a negative impact on mental-health from economic inactivity in the present period, with significance of 10%.

The negative mental health impacts associated with the transition from employed/self-employed to unemployment and long-term sickness is significant at 1% level for both men and women. The effect size in the case of both transitions is higher for men in the previous period, but in the present period, while the impact of unemployment is higher for men, the impact of long-term sickness for the present period is seen to be higher in women.

Transitioning from economically inactive into employed/self-employed is seen to be associated with an improvement in mental-health levels for both men and women when both periods are considered and the effect size is higher in men. The transition from economically inactive into long-term sickness or unemployment are indicative of poorer mental-health, and are seen to affect men more than women in the case of transitioning into unemployment. In the case of a transition from economically inactive into long-term sickness, women are affected more. All the results for transitions from economically inactive are significant at 1%.

In the case of a transition from either unemployment or long-term sickness into the employed/self-employed status, the improvement in mental-health is seen to have higher effect sizes for women. The results for these transitions are all significant at 1%.

The control variables show that general health impacts on women are consistently higher for all health levels, and the significance levels for men and women are at 1%. In the case of marital status, separation affects men more than women with a significance level of 5%, while the result is insignificant for women. The death of a partner negatively impacts women more than men with a significance level of 1%, while for men the level of significance is 5%. Inclusion of a lag period shows that income has a slightly higher effect size for men than women, both with 1% levels of significance, implying better mental-health with higher incomes. The full results are presented below in Tables 13 and 14.

Table 13: **Model 2A - Fixed Effects for Men & Women Sub-Samples**

VARIABLES	FE-Men-Model 2A	FE-Women-Model 2A
Labour Market Transitions = 2, Remains Unemployed	1.330***	1.191***
	(0.143)	(0.177)
Labour Market Transitions = 3, Remains Long-term Sick	1.730***	1.350***
	(0.216)	(0.206)
Labour Market Transitions = 4, Remains Economically Inactive	-0.368***	-0.0194
	(0.0913)	(0.0645)
Labour Market Transitions = 5, Unemployed to Employed/Self Employed	-0.525***	-0.764***
	(0.0957)	(0.128)
Labour Market Transitions = 6, Unemployed to Long Term Sick	2.591***	2.113***
	(0.298)	(0.337)
Labour Market Transitions = 7, Unemployed to Economically Inactive	-0.210	0.0819
	(0.178)	(0.144)
Labour Market Transitions = 8, Employed/Self Employed to Unemployed	2.180***	1.919***
	(0.126)	(0.164)
Labour Market Transitions = 9, Employed/Self Employed to Long Term Sick	3.955***	3.184***
	(0.332)	(0.308)
Labour Market Transitions = 10, Employed/Self Employed to Economically Inactive	-0.783***	-0.143**
	(0.105)	(0.0708)
Labour Market Transitions = 11, Long Term Sick to Employed/Self Employed	-1.367***	-1.466***
	(0.380)	(0.382)
Labour Market Transitions = 12, Long Term Sick to Unemployed	1.177***	1.661***
	(0.293)	(0.349)
Labour Market Transitions = 13, Long Term Sick to Economically Inactive	0.458*	0.0785
	(0.250)	(0.211)
Labour Market Transitions = 14, Economically Inactive to Employed/Self Employed	-0.703***	-0.434***
	(0.0959)	(0.0625)
Labour Market Transitions = 15, Economically Inactive to Unemployed	0.814***	0.682***
	(0.169)	(0.152)
Labour Market Transitions = 16, Economically Inactive to Long Term Sick	1.104***	1.409***
	(0.322)	(0.234)
General Health Level = 2, Good	0.611***	0.895***
	(0.0353)	(0.0376)
General Health Level = 3, Fair	1.811***	2.558***
	(0.0589)	(0.0605)
General Health Level = 4, Poor	4.262***	5.236***
	(0.123)	(0.103)
Marital Status = 2, Married or Civil Partnership	0.0977	-0.0356
	(0.0863)	(0.0965)
Marital Status = 3, Separated or Divorced	0.307**	0.126
	(0.135)	(0.134)
Marital Status = 4, Widowed or Surviving Partner	0.767**	1.727***
	(0.348)	(0.254)
Highest Education Levels = 2, Other Higher Degree	0.328	-0.191
	(0.234)	(0.195)
Highest Education Levels = 3, A Level	-0.0757	-0.255*
	(0.149)	(0.138)
Highest Education Levels = 4, GCSE	-0.0641	-0.0965
	(0.179)	(0.165)
Highest Education Levels = 5, Other Qualification	-0.0125	0.212
	(0.269)	(0.270)
Highest Education Levels = 9, No Qualification	-0.233	0.171
	(0.278)	(0.275)
Log Household Income Per Capita	-0.132***	-0.124***
	(0.0287)	(0.0296)
Number of Children	-0.0301	0.00986
	(0.0328)	(0.0333)
Age Bands = 2, Aged: 26-35	0.426***	0.209**
	(0.0912)	(0.0945)
Age Bands = 3, Aged: 36-45	0.647***	0.285**
	(0.128)	(0.129)
Age Bands = 4, Aged: 46-55	0.492***	0.266*
	(0.156)	(0.158)
Age Bands = 5, Aged: 56-65	0.0373	-0.146
	(0.184)	(0.188)
Constant	21.99***	22.94***
	(0.283)	(0.300)
Observations	134,246	166,112
R-squared	0.052	0.055
Number of Individuals	30,548	36,674
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: **Model 2B - Fixed Effects for Men & Women Sub-Samples**

VARIABLES	FE-Men-Model 2B	FE-Women-Model 2B
Labour Market Status = 2, Unemployed	0.814***	0.682***
	(0.169)	(0.152)
Labour Market Status = 3, Long-term Sickness	1.104***	1.409***
	(0.322)	(0.234)
Labour Market Status = 4, Economically Inactive	0.458*	0.0785
	(0.250)	(0.211)
Labour Market Transitions = 2, Remains Unemployed	0.516***	0.509**
	(0.191)	(0.207)
Labour Market Transitions = 3, Remains Long-term Sick	0.627**	-0.0582
	(0.300)	(0.234)
Labour Market Transitions = 4, Remains Economically Inactive	-0.826***	-0.0978
	(0.243)	(0.204)
Labour Market Transitions = 5, Unemployed to Employed/Self Employed	-0.525***	-0.764***
	(0.0957)	(0.128)
Labour Market Transitions = 6, Unemployed to Long Term Sick	1.487***	0.704*
	(0.397)	(0.370)
Labour Market Transitions = 7, Unemployed to Economically Inactive	-0.669**	0.00341
	(0.289)	(0.241)
Labour Market Transitions = 8, Employed/Self Employed to Unemployed	1.367***	1.237***
	(0.197)	(0.212)
Labour Market Transitions = 9, Employed/Self Employed to Long Term Sick	2.851***	1.775***
	(0.429)	(0.365)
Labour Market Transitions = 10, Employed/Self Employed to Economically Inactive	-1.241***	-0.221
	(0.262)	(0.215)
Labour Market Transitions = 11, Long Term Sick to Employed/Self Employed	-1.367***	-1.466***
	(0.380)	(0.382)
Labour Market Transitions = 12, Long Term Sick to Unemployed	0.363	0.979***
	(0.323)	(0.367)
Labour Market Transitions = 14, Economically Inactive to Employed/Self Employed	-0.703***	-0.434***
	(0.0959)	(0.0625)
General Health Level = 2, Good	0.611***	0.895***
	(0.0353)	(0.0376)
General Health Level = 3, Fair	1.811***	2.558***
	(0.0589)	(0.0605)
General Health Level = 4, Poor	4.262***	5.236***
	(0.123)	(0.103)
Marital Status = 2, Married or Civil Partnership	0.0977	-0.0356
	(0.0863)	(0.0965)
Marital Status = 3, Separated or Divorced	0.307**	0.126
	(0.135)	(0.134)
Marital Status = 4, Widowed or Surviving Partner	0.767**	1.727***
	(0.348)	(0.254)
Highest Education Levels = 2, Other Higher Degree	0.328	-0.191
	(0.234)	(0.195)
Highest Education Levels = 3, A Level	-0.0757	-0.255*
	(0.149)	(0.138)
Highest Education Levels = 4, GCSE	-0.0641	-0.0965
	(0.179)	(0.165)
Highest Education Levels = 5, Other Qualification	-0.0125	0.212
	(0.269)	(0.270)
Highest Education Levels = 9, No Qualification	-0.233	0.171
	(0.278)	(0.275)
Log Household Income Per Capita	-0.132***	-0.124***
	(0.0287)	(0.0296)
Number of Children	-0.0301	0.00986
	(0.0328)	(0.0333)
Age Bands = 2, Aged: 26-35	0.426***	0.209**
	(0.0912)	(0.0945)
Age Bands = 3, Aged: 36-45	0.647***	0.285**
	(0.128)	(0.129)
Age Bands = 4, Aged: 46-55	0.492***	0.266*
	(0.156)	(0.158)
Age Bands = 5, Aged: 56-65	0.0373	-0.146
	(0.184)	(0.188)
Constant	21.99***	22.94***
	(0.283)	(0.300)
Observations	134,246	166,112
R-squared	0.052	0.055
Number of Individuals	30,548	36,674
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Test for Significant Differences between Men and Women

As previously done, we also test for significant differences between the estimated impacts of labour market transitions on mental-health between men and women. We use a pooled regression specification to simultaneously estimate the effects for both men and women and test for significant differences in the estimates between genders. These results, shown as p-values for the test, are shown below in Table 15.

Table 15: **Test for Significant Differences between Genders - Model 2A**

Variable	**Prob >chi2**	**Significant Differences**
REMAINS UNEMPLOYED	0.178	No
REMAINS LONGTERM_SICK	0.005	**1%**
REMAINS ECO_INACTIVE	0.011	**5%**
UNEMPLOYED_TO_EMP_SELFEMP	0.122	No
UNEMPLOYED_TO_LONGTERM_SICK	0.090	**10%**
UNEMPLOYED_TO_ECO_INACTIVE	0.254	No
EMP_SELFEMP_TO_UNEMPLOYED	0.642	No
EMP_SELFEMP_TO_LONGTERM_SICK	0.119	No
EMP_SELFEMP_TO_ECO_INACTIVE	0.007	**1%**
LONGTERM_SICK_TO_EMP_SELFEMP	0.463	No
LONGTERM_SICK_TO_UNEMPLOYED	0.036	**5%**
LONGTERM_SICK_TO_ECO_INACTIVE	0.066	**10%**
ECO_INACTIVE_TO_UNEMPLOYED	0.184	No
ECO_INACTIVE_TO_LONGTERM_SICK	0.471	No
ECO_INACTIVE_TO_EMP_SELFEMP	0.162	No

As seen from the above table, the estimated effects for men and women are not statistically different to each other in the case of remaining unemployed and for many of the labour market transitions over two periods. We see a significant difference between genders for those remaining in long-term sickness and for a transition from employed/self-employed into economically inactive at the 1% level of significance. For those that remain in economic inactivity or transition from long-term sickness into unemployment, the differences between men and women are significant at the 5% level. A transition from unemployment into long-term sickness and a transition from long-term sickness into economic inactivity shows significant differences between men and women at the 10% level.

2.5 Conclusions

This research investigated the impact of labour market status and labour market transitions on self-reported mental well-being scores. The models first incorporated the contemporaneous labour market status of an individual, which included all the possible information that was present in the BHPS and US surveys. The baseline levels of mental-health associated with each labour market status showed employed individuals were in better health when compared to their unemployed and long-term sick peers. Subsequently the categories within the labour market were combined in-order to provide a base on which we could generate labour market transition variables. The combined labour market status in model 1B showed similar results to model 1A with unemployed and long-term sick individuals having worse off mental-health scores over employed peers. These results are closely in tune with existing findings by Jackson and Warr (1984), Theodossiou (1998), Bartley et al. (2006), Clark (2003) and McKee-Ryan et al. (2005).

In model 2A, we generated labour market transitions to represent an individuals interaction with the labour market over two consecutive time-periods and checked for mental-health impacts from these changes in labour market status. The incorporation of labour market transitions to the regression models showed us that accounting for mental-health over two time-periods has remarkably different estimated coefficients. The results show that the negative impact on mental-health moderate when individuals have remained in unemployment and long-term sickness over two periods. Of particular note are the transitions out of employment that reduced mental-health levels and transitions into employment that improved mental-health. Similar results showing the negative impacts of job loss on mental-health and improved mental-health associated with re-employment are seen in Joelson and Wahlquist (1987), Dooley et al. (1994), Weich and Lewis (1998), Winkelmann and Winkelmann (1998), Montgomery et al. (1999), Wadsworth et al. (1999), Murphy and Athanasou (1999) and Fryer and Fagan (2003).

Asymmetry in the effect sizes were seen in these labour market transitions, with larger estimated effects for negative impacts. The findings of asymmetric impacts on mental-health stemming from labour market transitions and their reverse transitions are also aligned with the findings of Frijters et al. (2011). Prospect theory, proposed by Kahneman (1979) provides a theoretical framework to interpret these results, as individuals are often loss averse with a negativity bias as also elaborated in Baumeister et al. (2001).

Also of relevance is that moving into and out of long-term sickness with respect to employment has the highest estimated effect size on mental-health in the expected directions. The transitions between employment and unemployment also had pertinent effect sizes, but these were lower than that seen in the case of long-term sickness.

In model 2B, we modified the regression specification to see the impact of labour market transitions over two time-periods on mental-health separately for the current year and the previous year. This also led to interesting results that showed the presence of partial adaptation to unemployment and long-term sickness over two time-periods. Adaptation results of a similar nature was seen in Clark and Oswald (1994) and Frijters et al. (2011). However, in the case of the present research we limited the evaluation of the changes in mental-health levels over two time-periods. As noted by Clark and Georgellis (2013) the significant negative effects of unemployment is therefore likely to persist to some degree for a longer period of time. Further, the mental-health impact of remaining in long-term sickness which was found significant over two time periods was seen to be insignificant for the previous time period.

In terms of robustness checks we compared the Pooled OLS estimators to the FE model to check if the results varied greatly. The results were overall consistent with the FE model and estimates were generally biased upwards in OLS. A possible reason for this is that the coefficients estimated in OLS might capture the effects of fixed traits which are not controlled for.

We also applied the regressions to sub-samples of men and women separately to see if gender disparity existed and was able to see some interesting results. Men were found to be impacted more in the case of transitioning into unemployment and long-term sickness when employment was lost, but women enjoyed increased improvements in mental-health while gaining employment from an unemployed or long-term sick status. The tests for significant differences in the estimates between genders revealed that unemployment and remaining in unemployment was not a statistically different result for men and women.

In summary, we find clear evidence of the mental-health impacts from labour market transitions to be asymmetric. In general, the negative impacts were seen to be higher than the positive impacts. This is logical and consistent with our expectations since losing a job and subsequently finding re-employment ought not to be a net positive impact for an individuals' mental wellbeing.

The results also suggests that policy makers attempting to improve mental-health levels of individuals in the labour market, would be advised to improve the chances of work for long-term sick for the best potential outcome. While traditional policies have attempted to reduce unemployment without much attention being paid to long-term sick individuals in the labour market, a rethink may be of value. Finally, the evidence also seems to suggest that mental-health levels of individuals in the labour market show some signs of adaptation with lag status having a moderating impact on mental-health levels. Therefore, any policy intervention should ideally have a short gestation period to be effective, given the signs of adaptation seen.

2.5.1 Future Research

While we have considered mental-health levels associated with labour market status and transitions, we have not accounted for possible selection effects and reverse causality in the current research. The pool of unemployed individuals may suffer from lower mental-health due to several reasons. To elaborate, unhealthy workers are more likely to become unemployed and those in better health more likely to gain re-employment. Further, individuals in poor mental-health may take longer periods to find re-employment. This leads to the unemployment duration for unhealthy workers to be likely longer than healthy workers. In addition, poor mental-health may in-fact cause the unemployment event as well. Therefore, deteriorating health levels may be a cause and not just a consequence of the job loss. Only with an exogenous reason for unemployment could we hope to investigate the causal impact of unemployment on health. The dataset used was the combined BHPS and US survey and the harmonised version of the variables raised challenges to control for possible selection effects and reverse causality over the full panel. Further, no investigation was made into the possible impacts that job quality and job security have on mental-health levels. As studies reviewed in this paper have shown, these are potentially important aspects that need further study.

Future research that looks at exogenous sources of unemployment, while controlling for impact of job quality and job security are necessary before we can make a definitive statement about causality in the relationship between labour market transitions and mental-health.

3 Evaluating the effects of In-Work Progression in the United Kingdom.

3.1 Introduction

The total annual expenditure for the UK Exchequer on welfare in 2015-16 exceeded £211 billion[6]. Of these, the benefits for low income earners for the same period amounted to over £27.1 billion with over 5.6 million claimants and unemployment benefits approximated £2.3 billion in 2015-16 with over 700,000 claimants (IFS, 2016, p12). These are significant numbers to the UK economy and represent over 11% of total GDP and 28% of total government spending, thereby constituting the single largest component of public expenditure (IFS, 2016, p11). Understandably therefore, a stated policy objective of the current Government is to bring about a reduction in the expenditure on welfare, specifically unemployment and low-income benefits.

In 2013, the Government of the United Kingdom rolled out a significant structural reform in the sphere of labour market benefits called Universal Credit (UC). Universal Credit envisages the transition of existing means-tested benefit schemes such as Income support, Income-based Jobseeker's Allowance, Income-related Employment and Support Allowance, Housing Benefit, Working Tax Credit and Child Tax Credit to be replaced under the overall UC umbrella. The rationale behind combining the existing means-tested benefits under a single UC benefit and administered solely by the DWP was to simplify the claimant's process, reduce error and fraud as well as create the institutional framework to encourage claimants to start work or increase working hours. The task of administering UC is with the Department for Work & Pensions (DWP) and the full roll out of UC is expected to be completed by 2022, though some delay is now likely on account of the recent Covid-19 lockdowns and disruption to DWP service delivery.

With the implementation of UC, the DWP has been involved in working with claimants who are currently in low paid work to stay in employment and support them to increase their earnings. Prior to UC, there was no expectation upon benefits claimants to progress. The DWP position is that *'anyone in receipt of Universal Credit with earnings below a certain threshold and who can reasonably be expected to earn more, should be required to seek opportunities for progression'* (SSAC, 2017, p21).

[6] This includes all social security expenditure such as Personal tax credits (£27.6b), Benefits for older people including Pensions (£98.2b), Benefits for families with children (£14.2b), Benefits for unemployed (£2.3b) and low income earners (£27.1b), Benefits for sick and disabled (£40.8b), Benefits for bereaved people (£597m) and Other benefits (£643m). Source: (IFS, 2016, p12)

When UC was first introduced in 2013, the original system for filing claims made available to claimants and work coaches was called the Live-service system. Live-service claims under UC was limited to individuals without children with low savings and seeking work. While new claims could be made online, any change in circumstances that affected eligibility had to be notified by telephone. Live-service was closed to new claims from January 2018 and subsequently by March 2019 it was closed to existing claimants[7].

Full-service which is also known as digital service, was gradually introduced to Jobcentres from 2016 onwards and allows work coaches to process UC claims for the full range of claimants. Full-service claimants are managed through a more advanced IT system and allows claimants to report changes in their circumstances through their online accounts. Additionally, the Full-service system allows for work coaches and claimants to communicate through an online journal that provides easy access to claimant history, thereby improving speed and efficiency of processing UC claims. Existing UC claimants on Live-service were transferred to Full-service within 3 months when Full-service was made available to a Jobcentre. By December 2018, Full-service was available in every Jobcentre across Great Britain.

Rules for accessing UC benefits involve Conditionality for each claimant based on the level of earnings. These vary for individuals, couples as well as other personal circumstances. A single claimant that earned more than the Conditionality Earnings Threshold (CET) of £1,137 a month was designated to the *'Working Enough'* group without any work-related requirements[8]. For individuals that earned less than the Conditionality Earnings Threshold of £1,137 a month, a further Administrative Earnings Threshold (AET) of £338 per month applied. Individuals below the AET were classified as *'Intensive Work Search'* with conditionality expectations on the claimant to look for work. Those above the AET but below the CET were classified as *'Light Touch'*. For Light Touch claimants the conditionality regime placed expectations of searching for more work and income progression on the claimant as well. For couples, the AET was set at £541 per month and household CET at £2,075 per month during the period of the In-Work Progression Trial[9].

[7] Source: https://www.gov.uk/government/publications/universal-credit-statistics-background-information-and-methodology/universal-credit-statistics-background-information-and-methodology

[8] The Conditionality Earnings Threshold during the period of the In-Work Progression Trial related to an individual claimant aged 25 years and working 35 hours per week at the National Minimum wage of £7.5 per hour. This is calculated as (35 Hours x £7.5 x 52 Weeks)/12 Months = £1137.5 Source: (Page 24) https://www.lbbd.gov.uk/sites/default/files/attachments/Universal-Credit-full-service-a-guide-for-LAs-v1.pdf

[9] Subsequent to the In-Work Progression Trial, the policy regime for Light Touch and the relevant Earnings Thresholds has now changed.

Thus, under UC, the DWP has been working towards the objective of assisting claimants achieve increased earnings and progress in their current or new employment. Work coaches in Jobcentres provide support and encouragement to claimants for achieving progression in work. The focus on enabling low income UC claimants to achieve earnings progression is a natural extension to what has traditionally been the role of a Jobcentre and the DWP in general.

3.1.1 Background to the In-Work Progression Trial

The DWP commenced with an In-Work Progression (IWP) Randomised Controlled Trial (RCT) in April 2015. The RCT was designed to *test the effectiveness of differing intensities of support and conditionality provided to current UC claimants in low-paid work or low-income households.* (DWP, 2018c, p3).

Claimants were first recruited into the IWP trial when they earned more than the AET but their earnings stay below the CET. This triggered the claimant to be allocated to the Light Touch regime which involves work coaches to contact them directly to bring them onto the trial. At this stage, a claimant is randomly allocated to any of the three support groups under the IWP trial. The three IWP support groups were defined according to the level of support received and associated conditionality. These included, the Minimal support group, Moderate support group and Frequent support group.

- **The Minimal Support Group** saw only two telephone interviews with the claimant, first on entry to the trial and the second after 8 weeks into the trial.
- **The Moderate Support Group** saw the involvement of the work coach for support to the claimant and work search reviews every 8 weeks.
- **The Frequent Support Group** saw work coach support for the claimant and work search reviews every 2 weeks.

It is also of note that in the Minimal support groups the agreed actions between the claimant and work coaches were voluntary, while in the Moderate and Frequent support groups these actions were mandatory and invited sanctions in the form of withheld benefits payments in some cases, if compliance was not maintained[10]. Essentially, the IWP trial

[10] Under the IWP Trial 3.1% of the Frequent support group, 2.6% of the Moderate support group and 1.5% of the Minimal support group received sanctions during the Trial. Low level sanctions on account of failing to attend a face to face or telephone meeting accounted for 91% of all sanctions (DWP, 2018c, p7)

was designed with the different levels of support and associated conditionality offered to the claimant as the primary treatment. The idea was to investigate how effective higher levels of support were for achieving IWP vis a vis the cost of administering the treatment.

From commencement in April 2015 in only 10 Jobcentres, the IWP trial was rolled out at a national level by December 2015. Recruitment into the IWP trial concluded in March 2017 and delivery of the interventions ended on 31 March 2018. The subsequent impact assessment of the IWP trials were based on two primary indicators. First, the actual impact on earnings for claimants in each of the three treatment groups. Second, the percentage of claimants who have seen an increase in wages of at least 10% since the trial. Additional soft outcomes such as changes in attitudes were also assessed. Claimants in all three groups were interviewed three months after the start of the IWP trial and subsequently 15 months after start date[11]. The initial results of the assessment showed that 52 weeks after the trial, Frequent and Moderate support groups earned £5.25 and £4.43 more than the Minimal support group. Further 2.9% and 2.4% of Frequent and Moderate support group claimants showed an increase in earnings over 10%. DWP (2018b).

3.1.2 Research Motivation

Numerous studies have previously investigated the relationship between low pay work and employment outcomes with varying conclusions. In particular, studies such as Uhlendorff (2006), Cappellari (2007), Clark and Kanellopoulos (2013), Cai (2014), Mosthaf (2014), Fok et al. (2015) show that individuals on low-paid work are at an increased likelihood of experiencing low pay in the future. However, Cai et al. (2018) presents evidence that low-paid workers have an increased probability of higher wages in future compared to lower wages in the future and as such low paid work can be considered as a springboard to higher wages in future.

This chapter builds upon the existing research conducted by the DWP for the evaluation of the DWP's In-Work Progression RCT. For the purposes of this research, the Minimal support group is also referred to as the comparison group since the RCT was designed without a no-intervention group. Denying IWP support to a set of claimants would not have been ethically justifiable from a policy perspective. In actuality, based on the fact that the Minimal support group received one phone call at the start of the IWP Trial and a subsequent phone call 8 weeks into the trial, the level of support received is low.

[11] The qualitative research survey included an extensive questionnaire that sought to assess claimant experiences with the ongoing IWP trial and work search reviews, employment history data as well as relevant individual and household level demographic data.

The estimated treatment effects from Frequent and Moderate support compared to the Minimal support group serves as a lower bound for the impact of the IWP trial versus a no treatment scenario.

The results of the initial DWP evaluation, while showing statistically significant levels of progression for Frequent and Moderate support groups compared to the Minimal support groups sheds no light on the distributional impacts of the earnings progression seen. Therefore, this research decomposes the results and attempts to identify where along the earnings distribution progression occurs. The distributional impacts of earnings progression is estimated for both Frequent and Moderate support groups separately. Specifically, the research tests if IWP support leads to better outcomes for those with lower levels of incomes, who may be more likely to drop out of work. This may provide evidence that IWP is successful in generating more stable jobs for those who are at the highest risk of being unemployed again. Consequently, this adds to the evidence base of active labour market policy research in the UK and is of direct policy relevance.

3.1.3 Research Objectives

The main objectives of this research are to estimate the treatment effects of IWP support through a difference in difference model. Subsequently, it will investigate distributional impacts of the earnings progression identified though quantile regression. The quantile regression allows us to check where along the weekly earnings distribution higher income progression is observed. Further, the dataset is subjected to sub-sample analysis to check if the results vary significantly between men and women, different age cohorts, for both Live-service and Full-service claimants and across different regions in the UK.

This chapter investigates the following research questions.

- **Research Question 1:** What are the estimated treatment effects from the IWP trial for Frequent and Moderate support groups compared to the Minimal support group 78 weeks after trial start date?
- **Research Question 2:** What are the estimated treatment effects from the IWP trial across selected quantiles in the earnings distribution?
- **Research Question 3:** Are there significant differences in the results between men and women, across age cohorts, Live-service and Full-service claimants, and across different regions in the UK?

3.2 Review of Literature

Previous labour market research has been extensive with studies covering both theoretical frameworks for ALMP analysis and empirical evaluations of the estimated impacts for ALMPs. This section covers the relevant literature related to ALMP evaluation, job search assistance, counseling and monitoring of low wage employed individuals, and differential impacts of ALMPs on women and across regions.

Within ALMP evaluations, studies have used both experimental and non-experimental methods to arrive at their estimated impacts. Non-experimental evaluation methods for ALMPs are discussed in Heckman and Robb Jr (1985), Moffitt (1991) and Regnér (2002). The main drawback of non-experimental ALMP research has been the need for strong assumptions about participant selection into ALMPs. As Heckman and Smith (1999) demonstrates, these assumptions are not always reflective of real-world conditions surrounding ALMP participation.

Evaluation studies using experimental data have increased in popularity in recent decades and are widely considered to be able to arrive at stronger causal estimates on account of the randomised nature of participation into the treatment. Evaluation strategies for ALMPs with experimental data are discussed in detail in LaLonde (1986) and Heckman and Smith (1995) and notable studies for estimating ALMP impacts from experiments include Bloom et al. (1997), Michalopoulos et al. (2000) and Hofmann et al. (2016). One limitation of ALMP evaluations that utilize experimental data has been the inability to predict the how the causal mechanisms of intervention and outcomes are linked. This has been discussed in Bredgaard (2015) where programme theory evaluation combined with impact evaluation is proposed as a solution to better understand the *how and why* of ALMP evaluations.

Previous ALMP evaluation research has also noted in their impacts seen on the different sub-groups of the population. As surveyed by Bergemann and Van Den Berg (2008), the impact of ALMP has differed for women when compared to the estimated effects for men. Additionally, Bell and Blanchflower (2010) and Verick (2009) show that the effects of unemployment are disproportionate across age cohorts with the youth at the highest risk of unemployment, especially during recessions.

Labour market evaluation research must also address the differences in ALMP design which broadly covers, Labour market training programmes, Public sector employment programmes, Private sector incentives and Job search assistance programmes. The IWP trial is closest to a Job Search Assistance programme where the treatment intervention provided is a Work Search Review between the Claimant and the Case Worker. For the present research, we start with a review of papers covering the theoretical framework of ALMP evaluation and subsequently review papers that have empirically evaluated the effects of ALMP. We first review empirical evaluations of ALMPs that use similar methodologies of quantile regressions and difference in difference models and then expand our discussion to papers covering wider aspects of relevance in ALMP evaluation and labour markets. The existing literature generally finds positive effects of job search assistance on the probability of exiting unemployment as well as positive effects of individual meetings between caseworkers and the unemployed. These are elaborated below.

3.2.1 ALMP Theoretical Framework

Snower (1995) provides a detailed theoretical framework in which ALMP can be evaluated and better understood. The author details the underlying theories of unemployment and provides an overview within which these can be analysed. Broadly, the discussion of theory behind unemployment falls under various schools of thought such as the laissez-faire, demand-management, supply-side, interaction between demand and supply-side policies and institutional policies. The laissez-faire stance views unemployment as the efficient outcome of the market system stemming from optimal decisions by job providers and job seekers. It calls for predictable policies and non-interference with business cycles and minimal government interventions except to deal with cyclical swings in unemployment. Demand-management policies are underpinned by Keynesian economics that advocates government intervention to create employment in the public sector and stimulate aggregate demand to generate employment in the private sector. Supply-side policies focus on job search and job matching challenges consequent to informational failures within the labour market. Interactive demand and supply side policies concern physical capital formation, low wage subsidies, payroll tax reductions, recruitment subsides and benefit transfers. Institutional policies seek to reduce labour union influences, reform of the wage bargaining system and reform of the unemployment benefit system. The paper also provides evidences that while none of the existing theories have been able to explain perfectly the historical data on unemployment across most developed economies such as the USA, Europe and OECD Countries, ALMP evaluation is probably best carried out through an analysis of the underlying theories.

Smith (2000) critically analyses the main challenges associated with the empirical methods used for evaluation of ALMP as identified in the existing literature. Notably, the author highlights the need for the use of better data in evaluation, the several challenges that face natural experiments making use of randomisation and the importance of general equilibrium effects that are often overlooked in ALMP evaluation. However, significant progress has been made by researchers in this area since. Potential complications to the proper interpretation of randomised experimental evaluations include, practical challenges of ensuring proper randomisation during ALMP implementation, the difficulty of identifying a suitable control group, dropout from the program among treatment group members, and substitution into alternative programs among experimental controls. Further, through the discussion of the potential general equilibrium effects stemming from ALMP the author highlights the challenges wherein these are often ignored or unable to be estimated accurately. Thus, making much of the estimations of the treatment effects of the ALMP unreliable. While models for estimation of the potential general equilibrium effects do exist, they are computationally complex requiring strong underlying assumptions about the functional forms of economic relationships and about the values of key economic parameters. The paper argues that the importance of general equilibrium effects has been likely under studied in the ALMP literature.

Calmfors (1994) provides an extensive micro-economic framework for analysis of the various effects of ALMP. The author uses a narrow definition of ALMP to include any measures that improve the functioning of the labour market which are directed towards the unemployed. These include measures that improve the matching process between job opportunities and job seekers, skill and job training to improve the employability of the unemployed, and direct job creation schemes in the public as well as private sector. The analytical framework elaborated highlights that the effects from ALMP are often diverse and not easily separable from each other. Notably, these include effects on job matching, labour force participation effects, effects on competition in the labour force, deadweight losses and substitution effects, displacement effects, productivity effects, work-test effects, general equilibrium tax effects, repercussions on other policies and other macro effects. The paper highlights with the use of the Analytical Framework that the *Net Effect* of an ALMP is often unclear and challenging to infer from theoretical reasoning alone leading to the need for more research. The paper suggests taking an approach wherein more focus on how ALMPs are designed may be crucial for improving labour market outcomes. The paper identifies compensation levels, extent of targeting, type of programme, the duration of programmes as well as coordination with the unemployment benefit system as crucial design features to be considered for effective ALMPs.

Bredgaard (2015) argues that ALMP evaluation requires an integrated framework that combines experimental methods with programme theory evaluations to understand how and why certain interventions are successful. ALMPs being inherently complex are difficult to evaluate and are often implemented in combination with other policies making purely experimental methods inadequate for a policy maker to understand the reasoning behind a particular policy's success. ALMP literature has generally identified three main effects from participation. These include motivation effects (increased job search obligations), locking-in effects (reduced job search intensity) and participation effects (improved qualifications). The identification of the exact reason an effect occurs is challenging but adds extra depth to the evaluation. However, indirect effects such as selection effects (some participants being selected at the expense of other participants), deadweight effects (employers hiring subsidised workers that they would have hired in any case), displacement effects (ALMP participants have higher employment opportunities at the cost of non-participants) and substitution effects (unintended effects beyond the intended outcomes) make causal interpretations of ALMP based on purely empirical methods challenging. The author suggests an integrated approach based on classification of interventions as simple, complicated or complex to better understand the context in which a successful ALMP is implemented. This allows policy makers to combine impact evaluation and programme theory evaluation, differentiate between implementation failure and theory failure, and further understand under what circumstances a certain ALMP works well or not for certain groups of participants.

Blundell and Dias (2009) provides an in-depth review of various evaluation methods used in empirical estimation. The authors highlight the adequacy, assumptions and data requirements for each approach with a focus on application in ALMP evaluation. For the present research, the discussion on Natural Experiment Approaches are especially relevant. Two key assumptions of these difference in difference methods involve, the common time effects across groups and no systematic composition changes within each group to estimate the average treatment effect by comparison of the differences in averages, before and after the intervention, between the treatment and control groups. Although the present research on IWP is based on randomized entry into the treatment, non-randomized assignment to treatment may lead to the presence of a selection bias on the observables and unobservables resulting in the non-comparability of the treatment and control groups. However, noncompliance or dropout from the treatment remains a challenge in randomized experiments. Difference in difference procedures do not control for unobserved temporary individual-specific shocks that may have an impact upon the decision of participation. The possible effect of the Ashenfelter's Dip (an empirically observed temporary dip in earnings just before entry into a training program leading to an expected higher earnings growth among the treated, causing an overestimation of the effects of participation) is relevant here when enrollment into the program becomes more likely if a temporary fall in the outcome variable is seen just prior to the start of the treatment. Thus, the estimate of the average treatment effect will be an overestimation in such cases. In the case of IWP, participants are randomly assigned to one of the treatment groups when earnings go above a certain threshold and this is an important aspect to consider in the final empirical specification used.

3.2.2 ALMP Empirical Evaluation

Theoretical models of ALMP evaluation make the important distinction between mean impacts and heterogeneous treatment effects stemming from welfare reforms. However, empirical evaluations of ALMPs often focus more on the mean impacts. The positive and negative impacts from ALMPs may average together and obscure the true extent of the effects. In this vein, empirical evaluations of ALMPs that consider potentially heterogeneous treatment effects find particular relevance to the present research. We start with a review of papers that are closely aligned in terms of methodology and research objectives. Subsequently, we cast a wider net and also discuss papers of broader relevance to labour market research.

Bitler et al. (2006) provide valuable insights on pursuing ALMP evaluation beyond the conventional estimates of their mean impacts. Using administrative data from the Connecticut Jobs First welfare program the authors investigate the quantile treatment effects and find substantial heterogeneity in the results compared with the mean treatment effects. The Jobs First ALMP was open only to women and implemented under a randomised framework during 1996 to 1997, and post-treatment data on earnings and welfare transfers was collected till the end of 2000. The paper first provides a theoretical framework for investigation of the impacts and predicts the quantile effects that are expected in line with labour supply theory. Notably, labour supply theory provides heterogeneous predictions on expected impacts from similar programs. While the mean impacts of the Jobs First welfare program was positive, the econometric evaluation finds important distributional differences in outcomes consistent with the theory. Specifically, the paper tests to see if the impact from the ALMP is constant across the distribution or whether some parts of the distribution have larger effects. The ALMP did not have an impact at the bottom of the earnings distribution, had a positive impact at the middle of the distribution and had a negative impact towards the top of the earnings distribution. The variations in quantile treatment effects considerably exceed the variations of mean effects across various sub-samples as well. Relevant to the present research, the results show that these empirical findings would have been missed if only the mean impacts of the Jobs first ALMP were assessed. Further, the estimation of quantile treatment effects (and mean treatment effects across sub-groups of participants) are especially useful if there are heterogeneous effects with opposite signs from ALMPs.

Bitler et al. (2008) investigate into quantile treatment effects of the Canadian Self Sufficiency Project (SSP) to estimate the distributional impacts on earnings, transfers and total income. The authors present a static as well as dynamic framework of labour supply theory to predict the impacts and subsequently evaluate the actual effects of the ALMP. The SSP was a randomly assigned welfare program between 1992 and 1995 that paid a supplemental income and the administrative data includes information on earnings and hours worked by beneficiaries. The paper evaluates how both hours and wages contribute to changes in earnings. The quantile treatment effects essentially show the difference in earnings between the treatment and control group at the quantile investigated. Thereby allowing to compare how SSP affected the lower end of the earnings distribution compared to the higher end of the earnings distribution. The evaluation results are in line with the predictions based on the theoretical framework presented in the paper and shows no impact at the lower end of the earnings distribution, positive impacts for the upper third of the earnings distribution with zero or negative impacts at the higher end of the earnings distribution. For transfer benefits, the positive impacts are found at the lower end of the transfer distribution. While for the income distribution, the positive impacts are concentrated towards the upper end. These results show considerable heterogeneity in ALMP effects that would be missed during an evaluation of the average effects alone. Notably, for the post SSP period studied, the distributional impacts are homogenous and show almost no change in the income distribution after the SSP payments cease.

Callaway and Li (2019) uses a distributional extension of the mean difference in difference assumption under a panel data setting to estimate the quantile treatment effect on the treated from increasing the minimum wage on unemployment rates in the US. The key rationale of the methodology is the potential usefulness that heterogeneity in the results may have for policy makers since programs that increase earnings at the lower tail of the earnings distribution while reducing earnings at the upper tail of the earnings distribution may be considered beneficial even if the average effect of the program is zero. The distributional difference in difference assumption requires that the distribution of change in untreated potential outcomes will not depend on whether the individual belongs to the treated or untreated group. The key methodological requirement is that the parallel trends assumption should hold on average to the entire distribution. The study also introduces a copula stability assumption that keeps the unknown dependence between the change in untreated potential outcomes and the initial level of untreated potential outcomes for the treated group as a constant over time. Essentially, this means that if higher earners tended to have larger increases in earnings in the past, then in the present without the treatment, the largest increases in earnings would go to the higher earners as well. This is indirectly tested using the additional pre-treatment period available in the panel. The empirical results show considerable heterogeneity in the results with the increase in minimum wage causing a negative impact on unemployment rates at lower quantiles and a positive impact at higher quantiles. In effect, there is a widening of the distribution of local unemployment rates subsequent to the increase in minimum wage. The overall results do not change much when controlling for covariates.

Pacheco et al. (2020) uses administrative data from New Zealand to estimate the transition probabilities between low pay and high pay workers. The authors define the lowest decile of earnings as low pay, between the lowest decile to the first quartile as intermediate pay and above the first quartile as high pay. The attachment to the labour market is defined in terms of number of months employed in low, intermediate or high pay and is used to define those with strong or weak attachment based on the duration of employment in the previous year. The analysis is conducted using a dynamic random effects multinomial logit model. Inherently, the assumption that low wage work serves as a gateway to higher wage employment is being tested in the study. The key finding of the paper is that that low wage workers have a much lower probability of shifting into higher pay by -20 percentage points in the next year when compared to those with higher pay. This result further deteriorates to -86 percentage points when the individual has a strong attachment to the labour market and has been in low wage work for the full preceding 12 months. Finally, low pay workers are at greater risk of falling into future unemployment as well. Overall, the results imply that low wage work itself does not improve future earnings progression and there is a need for development of human capital by way of trainings or skill developments to earn higher pay.

Claimants on the IWP trial are low income earners at the start of the trial, but often slip into subsequent periods of sporadic unemployment. Therefore studies that evaluate the impact of ALMPs on the unemployed also find relevance as they are closely related to the overall understanding of methodological issues pertinent to this research. These are discussed below.

Blundell et al. (2004) evaluates the effects of a well-known ALMP in the UK called the New Deal for Young People. This is a form of targeted ALMP that is designed to help shift young unemployed individuals into work and off Job Seekers Allowance welfare. The authors use the area-based piloting and age-based eligibility criteria which vary across individuals having similar unemployment spells to identify the treatment effects from the program. Specifically, the paper investigates for the existence of substitution effects between eligible and noneligible groups as well as for the general equilibrium effects from the ALMP. The New Deal involves job search assistance, wage subsidies, temporary government jobs and education and training for those aged between 19 to 24 and is mandatory. The study focusses only on job search assistance and wage subsidies to employers using a difference in differences approach to estimate treatment effects. Based on the age criteria and area-based piloting used in the New Deal, the paper uses different comparison groups to estimate treatment effects from the New Deal. The impact of substitution effects and general equilibrium effects on the overall treatment effects are potentially important as not taking these into consideration may lead to an overestimation of treatment effects. The study finds an increase in new employment for men attributable to the New Deal by about 5 percentage points with the treatment effects being larger in the beginning of the program. Therefore, the question of whether these gains will be sustained in the longer run remains to be measured.

Sianesi (2008) assesses the relative performance of six Swedish ALMPs in terms of employment probabilities and unemployment benefit dependency. The key aim of the paper is to assess if some programs are more effective than others with respect to their costs, if the effects vary over the short and long-term, and if they have been targeted on the unemployed beneficiaries optimally. The Swedish labour market policy includes unemployment benefits and several ALMPs. The six ALMPs investigated include, Labour Market Training, Work Experience Placement, Workplace Introduction, Relief Work, Trainee Replacement System and Job Subsidies. Thus, the spectrum of ALMP evaluated extends from those that attempt to increase employability through improvements in human capital to providing direct employment in public sector as well as incentivize private sector jobs to the unemployed ALMP beneficiaries. Notably, unemployment insurance although valid for upto 60 weeks, mandate the acceptance of a job offer if received. However, the extent of the unemployment benefits can be extended indefinitely with participation in any of the ALMPs evaluated. Thus, there could be strong work disincentives for those entitled to receive benefits. Through the use of matching based on unemployment duration, the treatment effects of each of the ALMPs are estimated. All the ALMPs investigated show a negative impact on job search in the short-term with employment probabilities decreasing by 15 to 25 percentage points. This result is attributed to the initial *Lock in Effects* which is an observed effect of other ALMPs as well. Longer term effects vary by ALMP but positive effects on employment probabilities are seen only for Job Subsidies.

On further investigation of the relative comparison of each ALMP, participants in Job Subsidies are again seen to enjoy higher employment probabilities as well as less likely to be on unemployment benefits. However, indirect general equilibrium effects such as the potential substitution and dead weight effects are ignored in the study.

Vikström et al. (2013) investigates the effects of a Danish ALMP that had multiple treatment arms and used randomised entry into treatment or control based on the date of birth of unemployed individuals by applying non-parametric bounds, thereby avoiding distributional assumptions related to identification. Treatment in the ALMP involved caseworker meetings and job search assistance. While random assignment to treatment and control groups ensure comparability of the two groups at the start of the programme, possible dynamic selection effects leads to identification issues at a later stage while estimating treatment effects. Dynamic selection refers to the situation wherein, treated individuals with characteristics having positive interaction effects are likely to leave unemployment early, thereby possibly creating an underestimation of the actual effects, while treated individuals with characteristics having negative interaction effects are more likely to leave unemployment later. This selective outflow confounds a simple comparison between treated and non-treated groups. The study uses average hazard rates over treated and control groups to investigate how soon treatment effects emerge and if they are sustained beyond the treatment period. The main results of the paper show that the ALMP was successful in reducing unemployment duration by a few weeks and has a significant positive effect on the transition probability out of unemployment. However, the results do not shed much light on how the effects of the treatment differ during the period of unemployment.

Hofmann et al. (2016) provides a causal evaluation on the use of Integration Agreements (mandatory contracts between unemployed individuals and their caseworkers) as a nudging instrument to enable quick reemployment for those under unemployment insurance benefits in Germany. The paper uses administrative data from the German Federal Employment Agency for males above 25 years and define four treatment groups based on the timing of the signing of the Integration Agreements. Using randomization at the individual level based on the timing of the Agreements and the extent to which the timing is announced in advance, the authors find a positive effect for entering employment within a year if the Agreements are signed immediately or within three months of entering unemployment. Further, analysis on individuals on predicted unemployment durations over six months are found to be the main driver of the results. Notably, the paper also surveys case workers to find that the majority do not believe that Integration Agreements support the unemployed in their job search. The results are robust to sub-samples and sensitivity analysis with the main conclusion of the paper being that Integration Agreements work better when signed early on for those expected to be in unemployment for longer durations over 6 months. For individuals with shorter expected unemployment durations, Integration Agreements do not have a significant effect on finding work.

A key focus of the present research is to check how the treatment effects from the IWP trial varied between men and women. Therefore, a review of previous ALMP research that focused on the evaluation of impacts on women are also carried out.

Bergemann and Van Den Berg (2008) survey the ALMP literature for Europe since 1999 specific to papers estimating individual treatment effects for women over 25 yeas of age with an aim to investigate how the effects differ between men and women. The authors note based on the previous literature that women are usually over-represented among the unemployed. Female labour supply is typically more responsive to wage changes over men on account of the Le Chatelier principle, where the additional options of housework, raising children and leisure play a part in women having more elastic supply functions. Thus, when wage rates increase women can substitute time towards work, instead of the other avenues that are not usually available to men. This phenomenon also plays a part in explaining the lower levels of labour force participation for women. The paper looks at the ALMP effects of skill training, job search assistance, monitoring and sanctions as well as employment subsidies for women and contrast the results with those of men. For skill trainings, the results for women are generally positive and significant with larger effect sizes to men. This is seen to be most evident for labour markets where female participation is already low. Job search assistance programs investigated also show higher positive effects for women over men where female labour market participation is relatively low. Similarly, for employment subsidies, the estimated effects for women are positive, significant and larger than men for labour markets with low female participation. However, as female labour market participation increases over time, the impacts of ALMPs for women are expected to decrease and approach the levels observed for men.

Macro economic effects on labour markets may also have a direct impact on the accuracy of ALMP evaluation. Therefore, we also consider papers that are related to such circumstances and may confound ALMP evaluations, especially across different regions.

Dauth et al. (2016) investigates the important question of whether micro-econometric ALMP evaluation fails to consider possible macro-econometric effects on the overall labour market and what the implications of this are. Beyond the direct impact on recipients, ALMPs could have spillover effects on non-participants, such as possible labour demand effects from reduced wages, Deadweight losses where participants would have been hired anyway without the ALMP intervention, Substitution effects which represent merely a redistribution of job opportunities from non-participants to ALMP participants and Displacement effects where firms not in receipt of the ALMP lose their competitiveness. Thus, moving beyond the question of whether the ALMP has individual benefits, the paper seeks to address the point whether the ALMP has had a net positive effect for all job seekers in a region. The effect of ALMPs for all job seekers in one region is evaluated using the variation in ALMP participation across regions over time. Using a generalized method of moments and a quasi-maximum likelihood function, the effect of ALMPs on regional matching efficiency is estimated. The study investigates 86 administrative regions in Austria with daily employment history of individuals in receipt of social security from 2001 to 2007. Several ALMP schemes in Austria (active job search, training, orientation, qualification, allowances, wage subsidies, socio-economic establishments in the non-profit sector, and apprenticeships) are investigated for their regional net effects. The results show that in the long run only a few ALMPs investigated (wage subsidies, apprenticeships, and non-profit sector interventions) show a net increase in job matches.

Dustmann et al. (2020) conducts an investigation to assess if there has been a reduction in employment consequent to introduction of a minimum wage in Germany. The minimum wage was uniform across the country and therefore different regions had varying effects with East Germany having a highest number of workers impacted. The paper uses a difference in difference methodology to estimate treatment effects across variations in individuals, region and firms. The policy is found to have increased wages of the lower wage workers relative to high wage workers without a reduction in employment prospects. Further, the minimum wage was found to have increased wages without reductions in employment in regions impacted more from the policy, relative to regions less affected from the minimum wage increase. Finally, the paper also tests if the minimum wage policy induces a shift in workers to reallocate to firms having higher quality in terms of wages paid, offering more full-time jobs and employing more skilled labour. The study acknowledges that the minimum wage policy was implemented in a period with a suitable macroeconomic environment witnessing steady economic growth and falling unemployment rates. The authors also provide reasoning that the mechanism underlying these effects include possible search frictions, monopsony power of firms to set wages lower than marginal product of labour and hire more workers, and potential product market frictions.

3.3 Data and Methodology

This section describes the dataset available and the research methodology used. The empirical strategy employed in this chapter draws from the methodology used in Bitler et al. (2006) and Bitler et al. (2008), and also considers the results seen in Bergemann and Van Den Berg (2008) as relevant.

3.3.1 Description of the Dataset

The dataset used for the present research is generated from the DWP administrative tables. The information available on participants who were randomly assigned into the trial includes the following, Encrypted National Insurance Number (NINO), Age, Gender, Date of Entry into IWP Trial, Region and Weekly Pay for a total of 130 weeks. The Region variable indicated where in the UK the claimant is from. The possible values include, North East, North West, Wales, London, Scotland, Central and Southern. Dummy variables include, Partner, Partner on Trial, Live-service, Full-service and each of the IWP support groups.

Participants in the IWP trial are identified though their entry into Light Touch and randomly assigned into Minimal, Moderate or Frequent support groups. The socio-economic variables are generated from the DWP systems and the weekly pay for 12 months prior to and 18 months after entry into the trial is merged through Real Time Earnings Information taken from the HMRC servers. The HMRC earnings information is linked with the DWP information at the participant level through the encrypted NINOs. The process of fetching and integrating earnings data with the DWP dataset requires a SAS batch run of the code and takes approximately 48 hours in total. Post data extraction from SAS, the dataset was used to check if the published results by the DWP are recreated with the use of Stata independently. The results of this exercise, shown below, returned the exact estimates as originally published by the DWP[12].

- Mean Earnings Difference of Minimal Support = £13.3608
- Mean Earnings Difference of Moderate Support = £15.06971
- Mean Earnings Difference of Frequent Support = £17.51598
- **Difference in Earnings (Frequent vs Minimal) = £4.155**
- **Difference in Earnings (Moderate vs Minimal) = £1.708**

[12] In-Work Progression Trial: Further Impact Assessment and Cost Benefit Analysis, October 2019. Department for Work & Pensions. (Pg 14 – Table 2.2) DWP (2019)

The above results provide assurances that transfer of data from HMRC servers through SAS and data cleaning methodology using Stata has been accurate. Importantly, the main result from previous DWP research has been the identification of Frequent support claimants experiencing a weekly income of £4.155 higher than Minimal support claimants and Moderate support claimants experiencing a weekly income of £1.708 higher than Minimal support claimants, at 52 weeks post start of the IWP trial.

Finally, some minor trimming of the dataset generated from HMRC information was conducted to achieve consistency in the dataset with the research objectives. Those aged below 18 and above 65 were dropped as well as claimants whose regional information was not provided. This resulted in less than 1% of the total claimants being dropped from the panel. Logical assertion checks were also conducted to see if there were any observations that needed to be addressed or were the result of any possible errors. Summary statistics for all variables were generated and are presented below in Tables 16 and 17. Detailed summary statistics of weekly pay for Minimal, Moderate and Frequent support groups are provided in Appendix A.2.1, A.2.2, A.2.3 and A.2.4 respectively.

Summary Statistics

Table 16: **Sample Sizes (%) - IWP Treatment Groups**

	Minimal %	**Moderate %**	**Frequent %**
Full Service	36.74	35.95	36.29
Live Service	63.26	64.05	63.71
Total	100.0	100.0	100.0
Male	42.14	42.09	42.83
Female	57.86	57.91	57.17
Total	100.0	100.0	100.0
Has Partner	17.28	18.06	17.41
No Partner	82.72	81.94	82.59
Total	100.0	100.0	100.0
Has Partner on Trial	4.41	4.37	4.61
No Partner on Trial	95.59	95.63	95.39
Total	100.0	100.0	100.0
North East	13.22	12.52	12.21
North West	28.68	28.62	28.41
London	21.08	20.80	20.96
Southern	14.38	13.37	13.43
Central	12.82	14.84	14.71
Wales	2.94	2.88	3.20
Scotland	6.89	6.98	7.08
Total	100.0	100.0	100.0

Table 17: **Sample Sizes (%) for Age Cohorts across IWP Treatment Groups**

Treatment	18-25	26-35	36-45	46-55	56-65	Total
Minimal (%)	17.6	28.6	19.9	21.5	12.4	100.0
Moderate (%)	15.8	27.9	20.4	23.0	12.9	100.0
Frequent (%)	16.5	28.2	20.2	22.5	12.5	100.0

3.3.2 Balancing Tests between Treatment Groups

Balancing Tests between the Minimal support group vs Moderate and Frequent support groups were conducted to check if the groups are comparable and on average have well balanced baseline values. The results are shown below in Table 18.

Table 18: **Balancing Tests – Minimal vs Moderate & Frequent Groups**

Variable	Const	Coef	Std Err	Significance Level
Age	0.3845169	-0.0008020	0.0002167	0.1%
Gender	0.3514264	0.0028965	0.0054539	No
Full Service	0.3508614	0.0061502	0.0056027	No
Live Service	0.3570116	-0.0061502	0.0056027	No
Partner	0.3543796	-0.0073006	0.0070799	No
Partner on Trial	0.3532759	-0.0040243	0.0130544	No
North West	0.3525615	0.0018717	0.0059649	No
London	0.3525154	0.0027737	0.0066223	No
Scotland	0.3534397	-0.0049204	0.0105771	No
Wales	0.3533364	-0.0079974	0.0157946	No
Central	0.3582979	-0.0369257	0.0077436	0.1%
Southern	0.3504957	0.0189237	0.0078262	5%
North East	0.3508791	0.0175023	0.0081012	5%

Sample Size: 31,456

Overall, the results of the balancing tests show that the differences in observed characteristics between the IWP trial arms are not significant for the majority of the variables. Given that randomisation was based on the last three digits of the claimants National Insurance number and implemented at the start of the trial, this is to be expected. Ensuring that all the groups are well balanced is important to the difference in difference methodology used in this chapter.

For Age, we see that there is a significant difference between the Minimal support group when compared to Moderate and Frequent support groups. However, the estimated magnitude of the coefficient is very small. Within different regions, the difference is seen to be significant for Central, Southern and the North East. However, the estimated coefficients are again found to be small overall and we see that the randomisation of the IWP trial has been effective in creating well balanced groups between the Minimal support and the Moderate and Frequent support groups.

3.3.3 Research Methodology

Economic theory related to labour supply predicts heterogeneity in the impacts of ALMPs. However, most ALMP evaluation research tend to focus only on mean impacts which average together the positive and negative effects. This creates the tendency for ALMP evaluation research to miss capturing the heterogeneous treatment effects. One way to address this concern is to create subgroups of the population (based on gender, age, education etc.) and estimate mean impacts for these groups. Another method is to assess the impact of the ALMP across the distribution of the outcome variable through estimation of the Quantile Treatment Effects.

The availability of weekly earnings data for randomised treatment and comparison groups meant that it was possible to compare the mean effects of the IWP trial between the trial groups and thereby estimate treatment effects directly. However, such an analysis may face challenges when extended to the quantiles of interest, which is the main focus of this research. Further, availability of experimental data provides a methodological advantage to the present IWP evaluation by allowing for estimation of heterogeneous treatment effects where the source of identification is already clear.

The present research uses a difference in difference methodology to assess the treatment effect of the IWP trial and undertakes a further assessment of the treatment effects observed at different parts of the income distribution through quantile regressions. Central to the difference in difference methodology used in this research is the assumption of Parallel Trends that is explicitly tested for below. Subsequently, the methodology of the research is explained in more detail along with the robustness checks conducted.

The balancing tests conducted in the previous section provided assurances that all the three IWP groups are well balanced on average, with respect to the observed characteristics in the data. Ensuring that the behavior of the three trial arms are similar during the pre-trial period is essential for arriving at convincing causal estimates from participation in the IWP trial. Since the dataset provided 52 weeks of pre-trial weekly earnings data, we are able to test the parallel trends assumption explicitly. The estimated mean impact from the Difference in Difference model shows the average increase in weekly income that a claimant in the Frequent Support and Moderate Support groups received, when compared to a similar claimant in the Minimal Support group.

Subsequently, we extend the test for the parallel trends assumption, which is originally conducted for the mean estimates, to cover the quantiles of interest as well. This provides assurances that the parallel trends assumptions holds between all three IWP groups across the quantiles investigated and that the proposed methodology for the present research is suitable. The present research therefore uses a Quantile Difference in Difference model to estimate the treatment effects from the IWP trial across the weekly earnings distribution of claimants. Essentially, we test to see if the impact of the IWP trial is constant across the weekly earnings distribution or if there are larger changes to weekly earnings at certain parts of the distribution. Therefore, the estimated results show the IWP treatment impact on the quantile of interest and how the claimant earnings distribution changes when IWP treatment is assigned randomly.

Finally, the difference in difference model used also allows us to maintain methodological consistency with the next chapter, where we estimate the treatment effects of the IWP trial at different time-periods in the observation period. Using a pooled specification with time dummies allows for more observations in the regression and an easy comparison of the treatment effects over time. This enables better overall comparisons of the results of the IWP trial evaluation from the thesis.

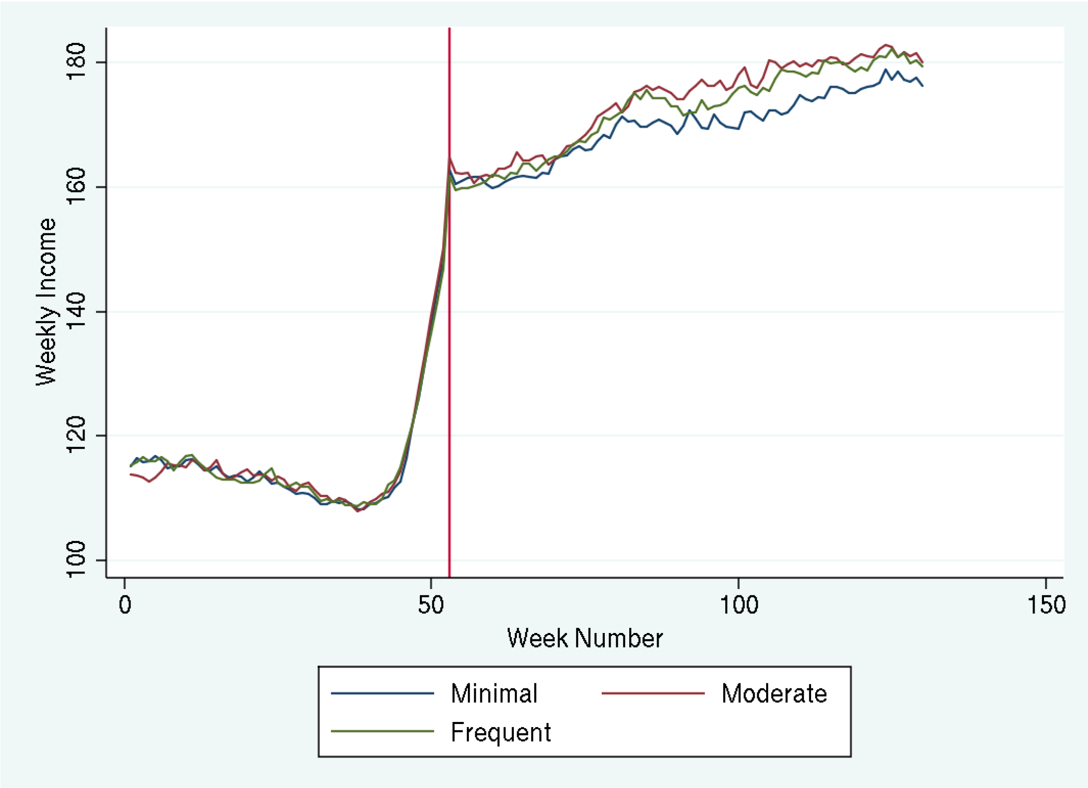
Tests for Parallel Trends

In order to utilise a difference in difference methodology for an assessment of the treatment effects from the IWP trial, the parallel trends assumption must be tested to ensure that all treatment groups have the same trend prior to the start of the IWP trial. This is done by the following methods.

1) Weekly Earnings Graph of IWP Support Groups

Mean income across all IWP groups should follow an identical trend and be visually similar prior to start of treatment in week 53. The dataset used includes a total of 130 weeks of claimant earnings data. Weeks 1 to 52 represent the pre-trial period, week 53 represents start of the IWP trial and weeks 53 to 130 show earnings data post start of the trial. The parallel trends assumption requires the three support groups to have an identical trend prior to start of the trial, which is expected to diverge after start of the trial. Figure 2 below shows the mean weekly earnings for all three IWP support groups.

Figure 2: **Mean Income – Minimal, Moderate & Frequent Groups**



Source: Generated from DWP Administrative Dataset. IWP Trial Start in Week 53

Prior to the IWP start date in week 53, all three treatment groups are observed as having a similar trend[13]. Further, a few weeks prior to the start of the treatment we see the mean earnings of all groups rise by about £40 per week. This is to be expected within the trial design that targets claimants whose earnings went above the AET, which is the entry trigger into the IWP trial.

2) Test for Parallel Trends in the Pre-Trial Period:

Income data is available for 52 weeks of earnings during the pre-trial period. This pre-trial data allows us to perform a placebo test, using the same model that is used to analyse the trial data. Thus, we test to see if there are any significant differences in weekly earnings across the IWP support groups from week 1 to week 52 prior to start of the trial.

[13]IWP Trial Start Date is not a single Date, but ranges from April 2015 to March 2017 per claimant. This makes the above comparison across different points in time for the present research.

If the average treatment effect is found to be statistically significant for the difference in difference during the pre-trial period, there is evidence to reject that prior to the IWP start date, the IWP groups had a similar trend. We therefore test the parallel trends assumption for the pre-trial period using the below regression model.

$$Y_{it} = \beta_0 + \beta_1 T_t + \beta_2 IWP_i + \beta_3 (T_t * IWP_i) + \epsilon_{it} \quad (5)$$

Where,

- Y_{it} is the Dependent Variable of Weekly Income.
- T is a Time Dummy: T = 0 for Week 1, else T = 1 for the Pre-Trial Period.
- IWP represents the Treatment Dummy. IWP = 0 for Minimal Support Group and IWP = 1 for Moderate or Frequent Support Groups.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.
- ϵ_{it} is the Error Term.

It is important to note that the above model estimates if there are significant differences in the pre-trial period between Minimal support versus the Moderate and Frequent support groups only at the mean. It does not provide assurances of the parallel trends assumption holding across the entire distribution of weekly earnings in the pre-trial period, which is separately tested next. The results for the test for parallel trends at the means are presented below in Table 19 and tabulated fully in Appendix A.2.5.

Table 19: **Results of Test for Parallel Trends in Pre-Trial Period**

Treatment Effect	Const	Coef	Std Err	Significance Level	No of Obs
Moderate Support	115.1522	1.671414	2.200782	No	1117168
Frequent Support	115.1522	0.138266	2.157141	No	1096108

In both cases the placebo test estimates average treatment effects in the pre-trial period that are insignificant for the Frequent and Moderate support groups compared to the Minimal support group. This is in line with our expectations and establishes the case that the parallel trends assumption holds for the all the IWP support groups in the pre-trial period at the mean.

Next, we check to see if the parallel trends assumption holds in the pre-trial period across the weekly earnings distribution for all quantiles investigated.

3) Test for Parallel Trends in the Pre-Trial Period across Quantiles:

The present research also investigates the treatment effects of the IWP trial at different quantiles of the income distribution. The use of a quantile difference in difference methodology requires that the parallel trends assumption in the pre-trial period holds not just at the mean, as demonstrated above, but across the entire distribution of weekly earnings. We test this explicitly at the 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 deciles using the below regression model in the pre-trial period.

$$Y_{\tau it} = \beta_{0\tau} + \beta_{1\tau}T_t + \beta_{2\tau}IWP_i + \beta_{3\tau}(T_t * IWP_i) + \epsilon_{\tau it} \tag{6}$$

Where,

- $Y_{\tau it}$ is the Dependent Variable of Weekly Income.
- T is a Time Dummy: T = 0 for Week 1, else T = 1 for the Pre-Trial Period.
- IWP represents the Treatment Dummy. IWP = 0 for Minimal Support Group and IWP = 1 for Moderate or Frequent Support Groups.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.
- τ represents the quantile being investigated.
- $\epsilon_{\tau it}$ is the Error Term.

The results of the above model for both Moderate and Frequent support groups are summarised below in Tables 20 and 21 and tabulated fully in Appendix A.2.6 & A.2.7. Notably, the investigation of the pre-trial parallel trends assumption across the distribution of weekly income show that the lower 3 deciles of claimants on the IWP trial had zero incomes in the pre-trial period and are dropped. This is on account of the trial design where entry into the trial is triggered when claimant earnings go above the AET but stay below the CET. The participants in the IWP trial are by definition low income earners and may have spells of zero earnings, which is evidenced by the presence of non-earners in the dataset. Some claimants in all three support groups were not earning during the IWP trial period and this is reflected by the nil weekly earnings in the dataset. This could be a result of holiday, loss of work contracts, temporary inability to continue work and other reasons. Claimants could be pushed into an Intensive Search regime if earnings go below AET and they could come back into the Light Touch regime under IWP when earnings go back above AET.

Table 20: **Results of Test for Parallel Trends across Quantiles in Pre-Trial Period - Minimal vs Moderate Support Groups**

Quantile	Const	Coef	Std Err	Significance Level
0.1	-	-	-	-
0.2	-	-	-	-
0.3	-	-	-	-
0.4	0.0000	1.507145	0.6273638	5%
0.5	65.8700	7.463230	5.8943210	No
0.6	113.4000	3.647308	2.9133200	No
0.7	163.1943	1.663574	2.5473330	No
0.8	225.0000	4.652863	3.1378260	No
0.9	302.8725	-1.454620	3.7965940	No

Table 21: **Results of Test for Parallel Trends across Quantiles in Pre-Trial Period - Minimal vs Frequent Support Groups**

Quantile	Const	Coef	Std Err	Significance Level
0.1	-	-	-	-
0.2	-	-	-	-
0.3	-	-	-	-
0.4	0.0000	1.421429	0.8581607	10%
0.5	65.8700	1.914360	4.7023770	No
0.6	113.4000	1.253502	3.0724050	No
0.7	163.1943	1.657150	2.8537180	No
0.8	225.0000	-1.201523	2.9634160	No
0.9	302.8725	-4.569489	3.7227990	No

From the above test, we find a significant result at the 0.4 quantile for both Moderate and Frequent support groups with 5% and 10% levels of significance respectively. Though we see that this is on account of the constant being close to zero for both groups at the fourth decile, representing zero income claimants at the start of the pre-trial period data. For all claimants at the median income level and above, there are no significant results and we conclude that the parallel trends assumption holds distributionally at the 0.5, 0.6, 0.7, 0.8, 0.9 deciles. Therefore, we exercise caution while interpreting results at the 0.4 quantile and limit our further research investigations to the 0.4 quantile and above.

Based on (DWP, 2018a, p29) work coaches felt that the high level of support offered by the IWP trial, especially under the Frequent Support group, could be unsuitable for low-income claimants and prone to a high degree of cancellations of Work Search Reviews (WSR). The IWP treatment is motivational in nature. When a claimant had zero earnings or close to zero earnings, the WSR is likely to be less effective than those who had higher weekly earnings. Higher earners tended to have better WSR meetings, more meaningful interactions with their work coaches, and ultimately benefit more from the IWP treatment. Therefore, we expect the efficacy of the IWP treatment to be stronger for claimants at higher levels of the weekly income distribution and much weaker for the non-earners and those at the lower end of the weekly income distribution.

Evaluation Methodology

Difference in Difference Framework

The difference in difference framework is estimated separately for Frequent support vs Minimal support and Moderate support vs Minimal support groups using the general specifications below.

$$Y_{it} = \beta_0 + \beta_1 T_t + \beta_2 IWP_i + \beta_3 (T_t * IWP_i) + \epsilon_{it} \tag{7}$$

Where,

- Y_{it} is the Dependent Variable of Weekly Income.
- T is a Time Dummy: T = 0 for Pre-Trial and T = 1 for Post-Trial Periods.
- IWP represents the Treatment Dummy. IWP = 0 for Minimal Support Group and IWP = 1 for Moderate or Frequent Support Groups.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.
- ϵ_{it} is the Error Term.

The above Difference in Difference model estimates the mean impacts from participation in the IWP trial. The results show the average increase in weekly income that a claimant in the Frequent Support and Moderate Support groups received, when compared to a similar claimant in the Minimal Support group.

Estimation of Quantile Treatment Effects

The mean differences between treatment and comparison groups as estimated by the previous model may conceal the heterogeneous impact of the IWP trial across the claimant earnings distribution. In order to investigate if the IWP treatment effects vary between lower and higher levels of the weekly wage distribution the research uses quantile regression within the difference in difference methodology explained in the previous section. We estimate the Quantile Treatment Effect on the Treated (QTT) under a Distributional Difference in Differences assumption. As demonstrated in the previous section, this requires the Parallel Trends assumption to hold on average to the entire distribution of weekly earnings being investigated.

The existing literature on quantile methods is extensive and Angrist and Pischke (2008) provides an excellent explanation of the interpretation of quantile regressions and estimation of quantile treatment effects. In the present case of the IWP trial, quantile regression is used to estimate treatment effects for a given quantile (τ) in the distribution of the outcome variable, conditional on the treatment. Specifically, the quantile's coefficient can be interpreted as the partial derivative of the conditional quantile of weekly earnings, with respect to the IWP treatment. This follows closely with the estimation strategy used in Bitler et al. (2006) and Bitler et al. (2008). The Quantiles (τ) investigated are 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 of the earnings distribution and the quantile treatment effect on the treated is estimated separately for Moderate support vs Minimal support and Frequent support vs Minimal support groups using the general specifications below.

$$Y_{\tau it} = \beta_{0\tau} + \beta_{1\tau}T_t + \beta_{2\tau}IWP_i + \beta_{3\tau}(T_t * IWP_i) + \epsilon_{\tau it} \tag{8}$$

Where,

- $Y_{\tau it}$ is the Dependent Variable of Weekly Income.
- T is a Time Dummy: T = 0 for Pre-Trial and T = 1 for Post-Trial Periods.
- IWP represents the Treatment Dummy. IWP = 0 for Minimal Support Group and IWP = 1 for Moderate or Frequent Support Groups.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.
- τ represents the quantile being investigated.
- $\epsilon_{\tau it}$ is the Error Term.

In the above model, we estimate the change in the weekly earnings distribution when claimants are randomly assigned to the IWP treatment groups. For any specific quantile, the quantile treatment effect is identified as the difference across treatment status in the quantiles of weekly earnings for the treatment and comparison groups. Thus, the estimated quantile treatment effect at the 0.5 quantile is calculated as the difference in median weekly earnings of the IWP treatment and comparison groups. The estimated effect does not identify the distribution of treatment effects, nor does it identify the impact of the IWP treatment for claimants at specific quantiles. More specifically, we do not assume rank preservation among claimants. In other words, the estimated results give the impact on the quantile, and not the impact on individuals who otherwise would have been in a specific quantile.

Under the randomised IWP trial, the quantile treatment effect is also identified as the difference in outcome (Y) weekly earnings across claimants in the treatment and comparison groups that, within their respective groups, fall in the quantile (τ) of Y. This can be represented as

$$QTE = Y^{T}_{(\tau)} - Y^{C}_{(\tau)} \tag{9}$$

Where,

- Y is the Outcome Variable of Weekly Income.
- T represents IWP Treatment Group for claimants in Frequent Support or Moderate Support Groups,
- C represents the IWP Comparison Group for claimants in Minimal Support Group,
- τ represents the quantile being investigated.

Additionally, we also check if the results varied significantly over sub-samples as a robustness check. The sub-samples investigated include, male vs female, age cohorts (18-25, 26-35, 36-45, 46-55, 56-65), Live-service vs Full-service claimants, and regional specific sub-samples.

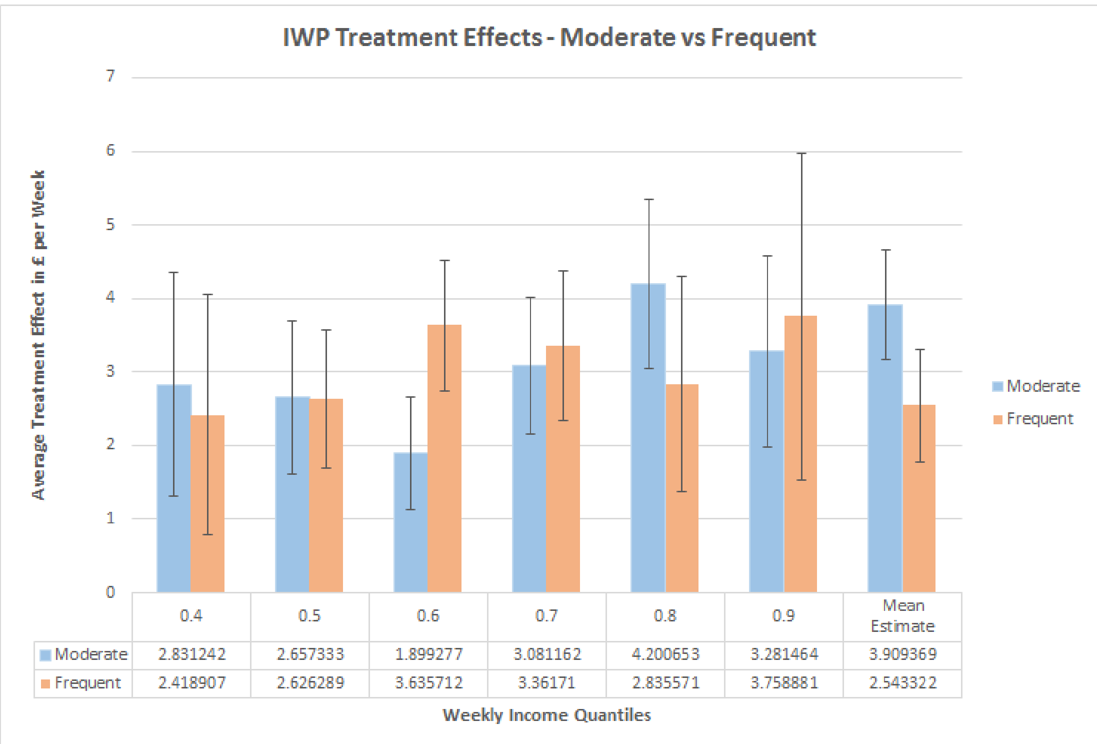
3.4 Results and Discussion

This section describes the results of quantile difference in difference regressions. The weekly income observations for the pre-trial period corresponding to 0.1, 0.2 and 0.3 quantiles have values of zero. This is on account of individuals not working prior to entry into the trial as well as some participants having irregular zero income weeks while on the trial. Therefore, we are unable to interpret the treatment effects seen at quantiles 0.3 or lower in the income distribution. The results discussed are only for the mean estimates and quantiles above 0.4. The discussion and graphical summaries of the results are shown below while the detailed tabulated results are found in Appendix A.2.8.

3.4.1 Difference in Difference Quantile Regression Results

The treatment effect of the IWP Moderate and Frequent support groups compared to the Minimal support group was plotted across the income quantiles investigated to get an idea of the variation in income progression. The results are shown in Figure 3 below.

Figure 3: **IWP Treatment Effects - Moderate vs Frequent**



We see that Moderate and Frequent support groups tend to show a marginally increasing trend of positive treatment effects at higher wage quantiles. All the results are significant at the 0.1% with vertical bars indicating two standard errors of the estimates. Overall, the results are in line with our expectations and the previously published DWP studies. The results for the mean estimate of all claimants show that the treatment effect of the Moderate support group has been higher than that of the Frequent support group. However, this includes the impacts from the claimants below the 0.4 quantile which cannot be accurately interpreted due to their pre-trial income observations being zero. The impact from the IWP trial has been broadly similar for Moderate and Frequent support groups.

Subsequently, we test to see if there is a significant difference between the estimated treatment effects at the investigated quantiles. The p-values for the test are presented below in Table 22 for Moderate and Frequent support groups with their levels of significance and highlighted in bold where we see a significant difference.

Table 22: **Test for Significant Differences between Estimates - IWP**

Moderate Support					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.6940	**0.0753**	0.7037	**0.0846**	0.6071
0.5	-	**0.0141**	0.3580	**0.0121**	0.3670
0.6		-	**0.0000**	**0.0000**	**0.0191**
0.7			-	**0.0023**	0.6970
0.8				-	0.1135
Frequent Support					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.6698	**0.0611**	0.1398	0.5625	0.1560
0.5	-	**0.0017**	**0.0797**	0.7316	0.2659
0.6		-	0.4361	0.1644	0.8967
0.7			-	0.2068	0.6009
0.8				-	0.1300

We see that the quantile treatment effects for the Moderate support group shows significant differences between lower and higher quantiles, especially with the 0.8 quantile. For Frequent support groups while there is a significant difference observed for lower quantiles with the 0.6 and 0.7 quantile, this does not extend to the higher quantiles.

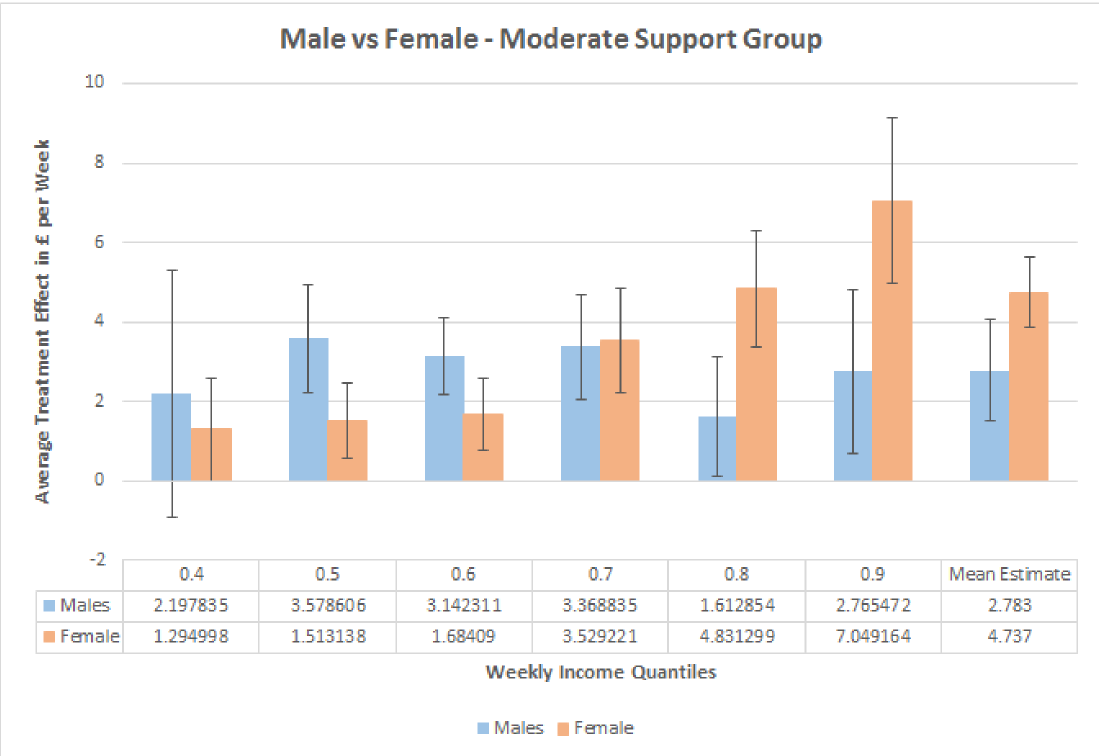
3.4.2 Male vs Female Results

The treatment effects of IWP were investigated separately for men and women to get an idea of how the trial has impacted both genders across the income quantiles. The quantile treatment effects for Moderate and Frequent support groups was plotted for males and females to get an idea of the variation in income progression. These are presented and discussed below for Moderate and Frequent support groups.

Moderate Support Group

In the case of Moderate support, both females and males have treatment effects that are significant. However, as shown below in Figure 4, females clearly have higher treatment effects associated with higher levels of the income distribution. Thus, females show a clear trend of increasing treatment effects as income levels rise beyond the 0.4 quantile. For males, the treatment effects do not show a clear trend at income levels above the 0.4 quantile. The 0.4 quantile result which shows a larger effect size for men over women, is however not significant for men. For the mean estimates, we see significant effects for men and women, with women having benefited more with an overall higher treatment effect through participation in the Moderate support group of the IWP Trial.

Figure 4: **Male vs Female – Moderate Support**



We analyse further to test if the estimated effects at each quantile are significantly different to each other and the results, shown as p-values, are presented below in Table 23. In the case of men, we see a significant difference between lower quantiles of 0.5, 0.6 and 0.7 with the 0.8 quantile. However, for women, we see highly significant differences between all the lower and higher quantiles investigated.

This result is particularly interesting as we see that women have not only benefited more from Moderate support compared to men, but also the estimated effects are significantly different between lower and higher incomes quantiles for women.

Table 23: **Test for Significant Differences between Estimates - Male vs Female - Moderate Support**

Males					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.2085	0.5177	0.4841	0.7413	0.7386
0.5	-	0.4532	0.7665	**0.0301**	0.4763
0.6		-	0.6462	**0.0055**	0.6565
0.7			-	**0.0033**	0.5697
0.8				-	0.1588
Females					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.5624	0.4653	**0.0000**	**0.0000**	**0.0000**
0.5	-	0.6324	**0.0000**	**0.0000**	**0.0000**
0.6		-	**0.0000**	**0.0000**	**0.0000**
0.7			-	**0.0028**	**0.0000**
0.8				-	**0.0004**

Frequent Support Group

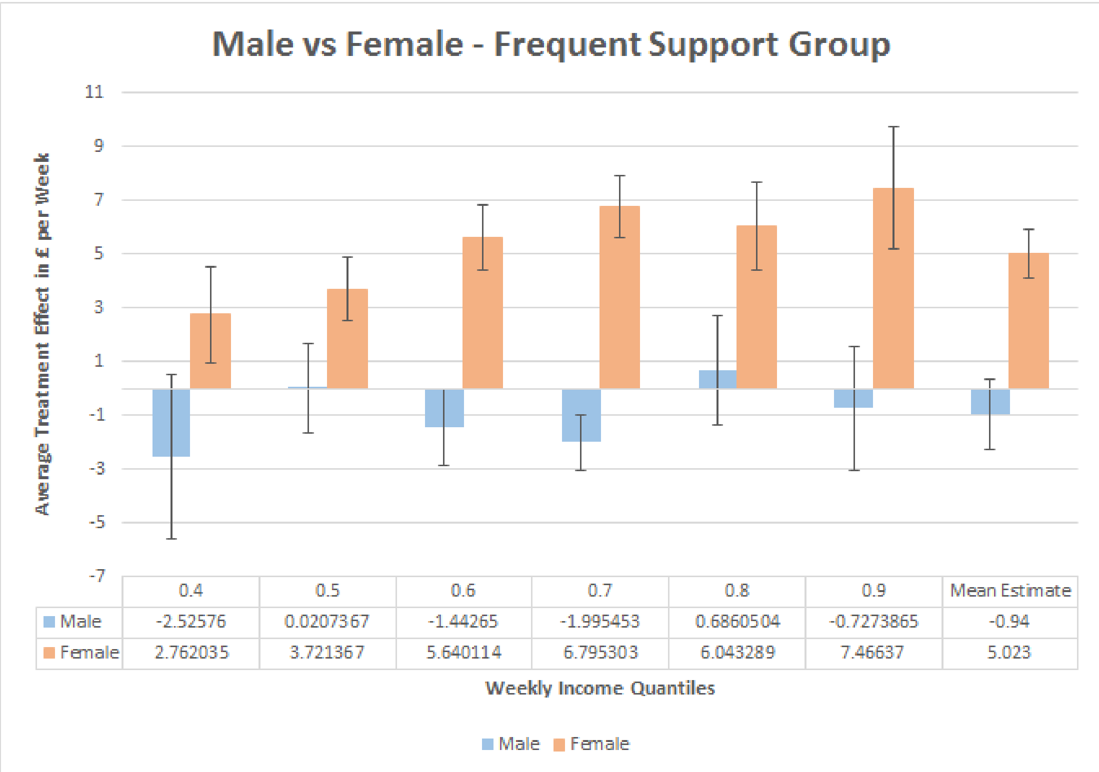
The investigation of the treatment effects from Frequent support across income quantiles for men and women separately showed very interesting results.

The estimated effects are positive and highly significant throughout for women. As with the case of Moderate support, women are found to have a clearly increasing treatment effect as income quantiles increase. The mean effect for women is also positive and highly significant from Frequent support. Compared to Moderate support, the overall effect sizes for women are larger in Frequent support. This is especially noticeable in the lower income quantiles.

For men, the effects are found to be significant only at the 0.6 and 0.7 quantile and the estimated effect from Frequent support is negative on the earnings progression of men.

This implies that men are less receptive to the Frequent support of the IWP trial which may have had a detrimental impact on their earnings. The mean estimate of the treatment effect on men is also found negative, but is not statistically significant. The wider standard error bands seen in the above figure for men also signify the statistical uncertainty of their estimated effects. These are presented below in Figure 5.

Figure 5: **Male vs Female – Frequent Support**



As in the previous section, we test the results for statistically significant differences between quantiles. Once again we find that in the case of women, there are highly significant differences between the estimated treatment effects of the lower and higher quantiles throughout. This is an important result as it shows the consistently positive effects that are observed in female participants on the IWP trial.

For men, we see that there are significant differences between the estimated treatment effects at lower and higher quantiles, but they cannot be reliably interpreted as the underlying effects were mostly found to be statistically insignificant. The p-values for the test are presented below in Table 24.

Table 24: **Test for Significant Differences between Estimates - Male vs Female - Frequent Support**

Males					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	**0.0088**	0.4259	0.7132	**0.0329**	0.3026
0.5	-	**0.0052**	**0.0026**	0.4289	0.5171
0.6		-	0.1711	**0.0018**	0.5149
0.7			-	**0.0001**	0.1839
0.8				-	**0.0757**
Females					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.0426	**0.0000**	**0.0000**	**0.0001**	**0.0000**
0.5	-	**0.0000**	**0.0000**	**0.0005**	**0.0001**
0.6		-	**0.0004**	0.4823	**0.0492**
0.7			-	**0.0645**	0.4382
0.8				-	**0.0395**

3.4.3 Live-Service vs Full-Service Results

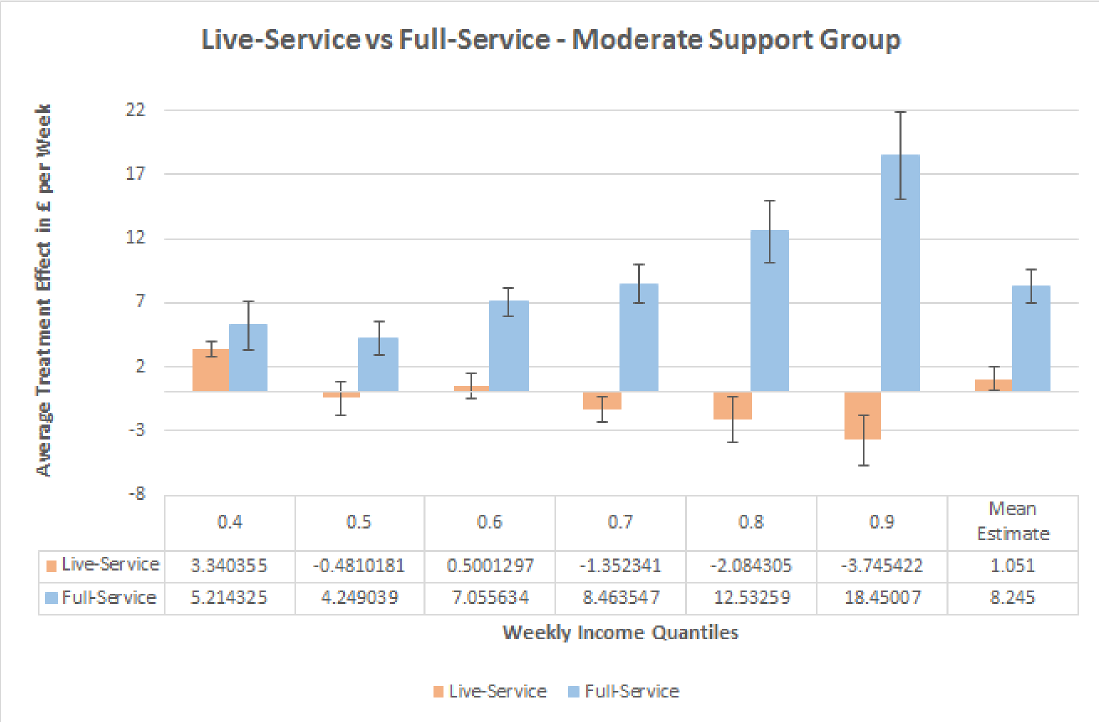
The results across income quantiles between Full-service and Live-service claimants for Moderate and Frequent support groups show significant variations between the two service groups and are elaborated separately below.

Moderate Support Group

Under Moderate support, Full-service claimants see steadily increasing improvements in income progression as wage quantiles increase over the 0.4 quantile. The highest treatment effect in the case of Full-service claimants is observed at the 0.9 income quantile. All the quantile results as well as the mean estimate for Full-service are positive and significant at high levels throughout. However, Live-service claimants are seen to have reduced levels of treatment effects as wage quantiles increase for the Moderate support group. We see a positive and significant treatment effect only at the 0.4 quantile and at the mean estimate. Further, the estimated effect at the 0.7, 0.8 and 0.9 income quantiles are negative and significant. While the estimation gives insignificant results for 0.5 and 0.6 quantiles.

This is a potentially important finding and insight into the possible reason for such a difference in outcomes between Live-service and Full-service claimants need further investigation and study. The effect of the IWP trial between Live-service and Full-service claimants under the Moderate support group are presented below in Figure 6.

Figure 6: **Live-Service vs Full-Service - Moderate Support**



To test the reliability of the results, we check these estimates further to see if they are statistically different to each other. The results of the test, shown as p-values, indicate that almost all quantile estimates are significantly different to each other and are presented in Table 25 below.

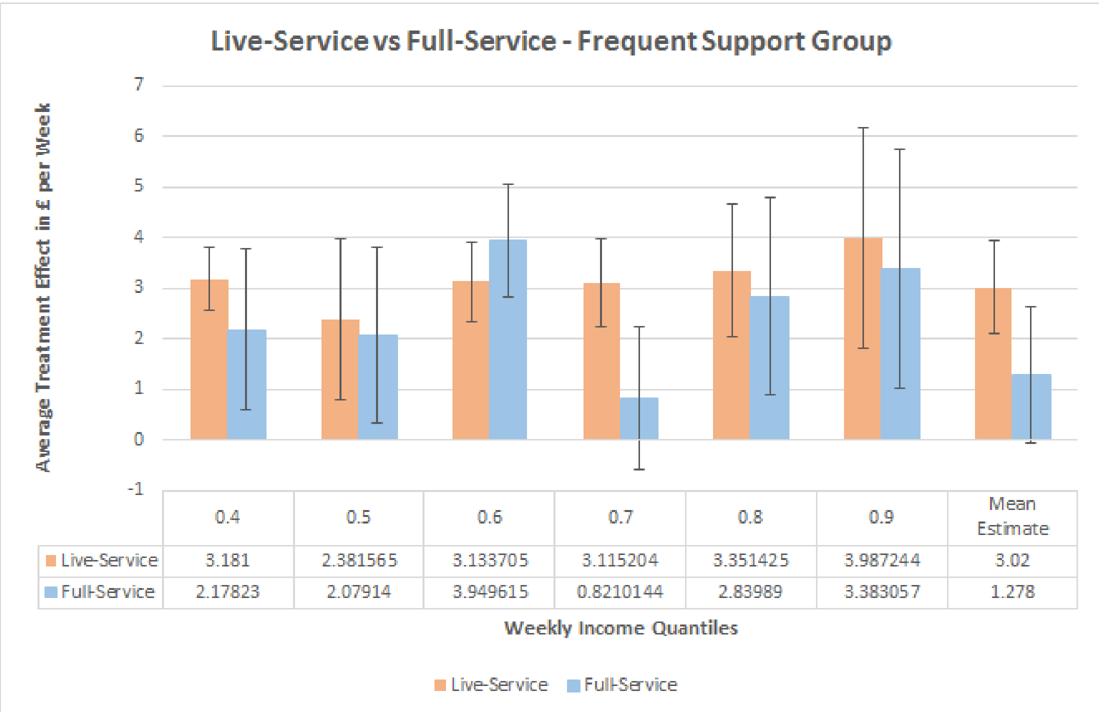
Table 25: **Test for Significant Differences between Estimates - Live-Service vs Full-Service - Moderate Support**

Full-Service					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	**0.0568**	**0.0095**	**0.0003**	**0.0000**	**0.0000**
0.5	-	**0.0000**	**0.0000**	**0.0000**	**0.0000**
0.6		-	**0.0006**	**0.0000**	**0.0000**
0.7			-	**0.0000**	**0.0000**
0.8				-	**0.0000**
Live-Service					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
0.5	-	**0.0172**	0.1275	**0.0161**	**0.0000**
0.6		-	**0.0000**	**0.0001**	**0.0000**
0.7			-	0.2996	**0.0039**
0.8				-	**0.0026**

Frequent Support Group

For the Frequent support group, the estimated effects for Live-service and Full-service claimants do not show a similar trend as we saw in the case of Moderate support. Live-service claimants have positive and highly significant results throughout all quantiles and at the mean estimate. They also show a gradually increasing trend for effect sizes at higher income quantiles from the median onward. For Full-service claimants the treatment effect of IWP Frequent support has been positive and significant, but the effect sizes are overall slightly smaller when compared to Live-service. The only exceptions are at the 0.6 quantile where Full-service claimants see a higher treatment effect over Live-service claimants and at the 0.7 quantile where we see sudden decline in the estimated effect for Full-service claimants, but the result is insignificant. Further, the mean estimate for Full-service is much smaller compared to the mean effect seen for Live-service claimants. These results are presented in Figure 7 below.

Figure 7: **Live-Service vs Full-Service - Frequent Support**



Similar to the previous results, we also test for significant differences between the estimated treatment effects at each quantile. The results, shown as p-values, are below in Table 26 and we find no significant differences across quantiles in the case of Live-service claimants. While, for Full-service claimants, there are significant differences across the lower and medium quantiles as well as the medium and upper quantiles investigated.

Table 26: **Test for Significant Differences between Estimates - Live-Service vs Full-Service - Frequent Support**

Live-Service					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.3449	0.9092	0.8979	0.8182	0.5052
0.5	-	0.1976	0.2792	0.2838	0.2452
0.6		-	0.9525	0.7394	0.4762
0.7			-	0.6016	0.3974
0.8				-	0.4521
Full-Service					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.7786	**0.0014**	**0.0172**	0.4865	0.3603
0.5	-	**0.0007**	**0.0241**	0.4180	0.3175
0.6		-	**0.0000**	0.1394	0.6372
0.7			-	**0.0095**	**0.0422**
0.8				-	0.5894

Interestingly we see that Full-service claimants have much better outcomes compared to Live-service claimants in the Moderate Support group throughout the income distribution and especially at higher levels of incomes. Whereas in the case of Frequent support, this result is reversed with Live-service claimants having better outcomes over Full-service claimants at all levels of the income distribution, except the 0.6 quantile and at the mean estimate.

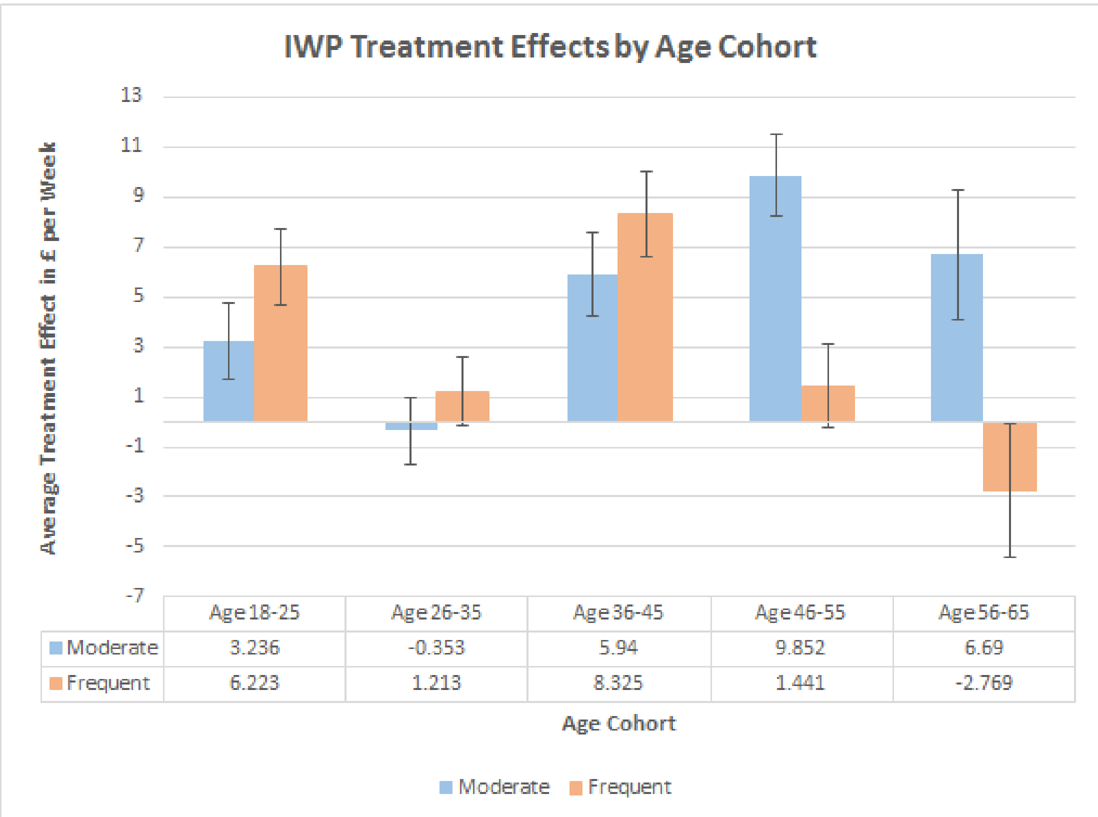
3.4.4 Age Cohort Results

The IWP treatment effects by age cohort are investigated next. Claimants below the ages of 18 and above 65 were trimmed from the dataset and age cohorts were defined as 18-25, 26-35, 36-45, 46-55 and 56-65.

The investigation of IWP treatment effects across age cohorts revealed interesting heterogeneity across treatment arms as well as age of the claimants. For the youngest cohort of ages 18-25, we see positive and highly significant outcomes for both Moderate and Frequent support groups. Though the estimated effect is higher in the case of Frequent support. Moderate support shows significant and positive treatment effects on incomes from the IWP trial for all age cohorts except for ages 26 to 35 where a negative effect was seen, but was insignificant. Moderate support continues to rise and deliver relatively higher treatment effects from claimants aged above 36 with a slight dip in treatment effects for the age cohort 56 to 65. The treatment effect seems to peak at ages between 46 to 55 for the Moderate support group.

For the Frequent support group, the lower age cohort of 18 to 25 shows a large treatment effect with the result being positive and highly significant. The estimated effects for claimants aged 26 to 35 are positive, but small in magnitude and only significant at 10%. Further, ages 36 to 45 shows a large and positive treatment effect that is significant at very high levels. Frequent support continues to outperform Moderate support for all age cohorts under the age of 45. There is, however, a change in the pattern of the treatment effect witnessed at age cohorts over 45 between Moderate and Frequent support groups. For ages above 45, the estimated treatment effect for the Frequent support group are significant and starts to show a notable decline with the IWP treatment effect going into negative territory for the oldest set of claimants at ages above 55. The age cohort results for Moderate and Frequent support groups are presented in Figure 8 below.

Figure 8: **IWP Treatment Effects by Age Cohort**

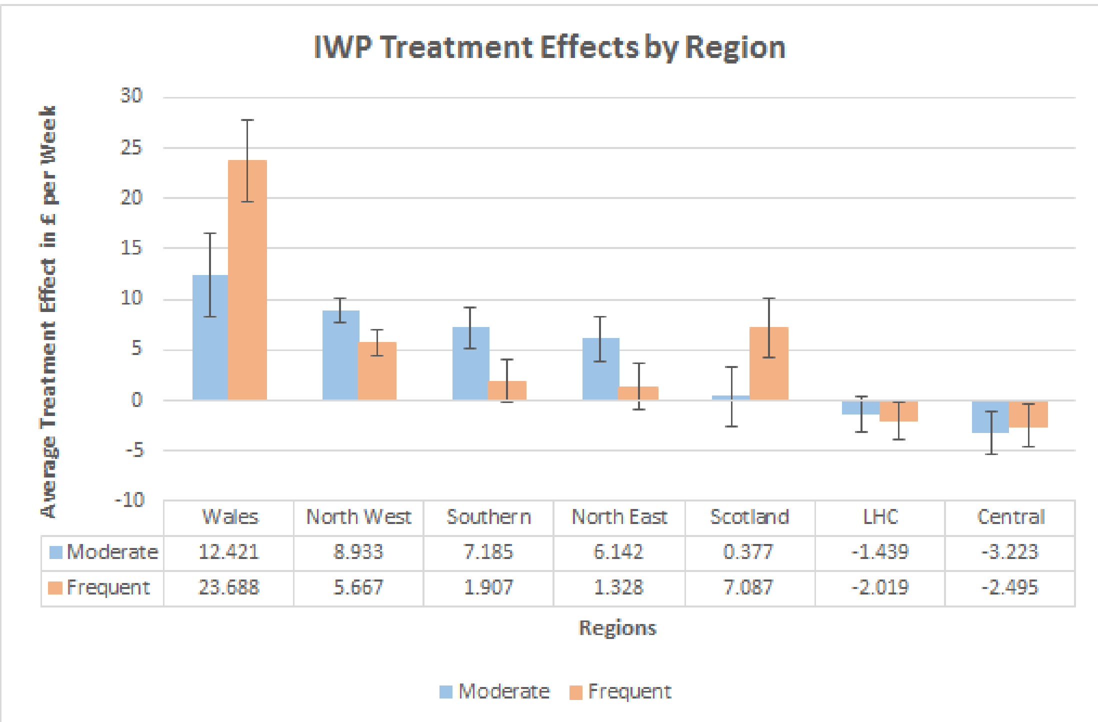


Overall, we see interesting trends that shows the suitability of the trial based on age of the claimants and the type of support received under the IWP trial. Specifically, we see that Frequent support has limited appeal to claimants above the age of 46 with negative effects for ages between 56 to 65. Discussions with DWP colleagues raised the suggestion that the frequency of the work search review intervention under Frequent support being every 2 weeks between the work coach and the claimant possibly results in a *nag* as opposed to a *nudge* and acts to demotivate older low income workers.

3.4.5 Regional Results

The IWP trial divided the United Kingdom into seven different geographical regions. This includes North East, Wales. North West, London (LHC), Scotland, Southern and Central. The treatment effects for claimants from each region are estimated through separate regressions for each regional sub-sample. The key point being investigated was to check if the IWP trial had significant differences across the different regions it was implemented. Differences in local labour market conditions could a priori explain this. Different levels of experience among work coaches that administered the IWP support could also have been a contributing factor as noted in (DWP, 2018a, p68-69). Figure 9 below shows the estimated treatment effects for Moderate and Frequent support groups for each region.

Figure 9: **IWP Treatment Effects by Region**



The Moderate support group showed positive and significant treatment effects in Wales, North West, Southern and North East regions. Central region showed a negative and significant treatment effect, while the estimated effect on London (LHC) and Scotland regions was insignificant.

Contrasting this with the Frequent support group shows us significant positive treatment effects for Wales, Scotland, North West and Southern regions. London (LHC) and Central regions are found to have significant and negative treatment effects. Finally, North East is seen to have an insignificant treatment effect in the case of Frequent support.

Overall, we see from the figure above that the results look a bit similar for both treatment groups. The highest IWP treatment effect seen was in Wales for Frequent and Moderate support groups. However, we also note that the sample size for claimants in Wales was lower than the rest of the regions. The North West region is also seen to have a positive and significant effect for both IWP support groups. Additionally, the Central region is found to have a significant negative treatment effect for both Moderate and Frequent support. This result raises the possibility that some differences in the method of administering the trial by work coaches may have had a part in the overall success of the trial and further investigation of possible best practices in some regions may be of future interest.

3.4.6 Further Investigations

As the investigation of the IWP treatment effects progressed, it was seen that the results were heterogenous by sex and age and therefore further investigations were conducted. The analysis revealed that females over the age of 35 showed particularly higher levels of income progression after participation in the IWP Trial.

This subset of older women was selected for further study to see if there were insights to be gained from a Policy perspective. The results for women aged above and below 35 years were further examined to see if there were significant variations between the Moderate and Frequent support groups over the weekly wage distribution, between Live-service and Full-service and across the various regions. As with the previous results, we refrain from interpretation of the income quantiles below 0.4 due to the pre-trial period consisting of non-earners and limit our discussion of results at income quantiles of 0.4 and more.

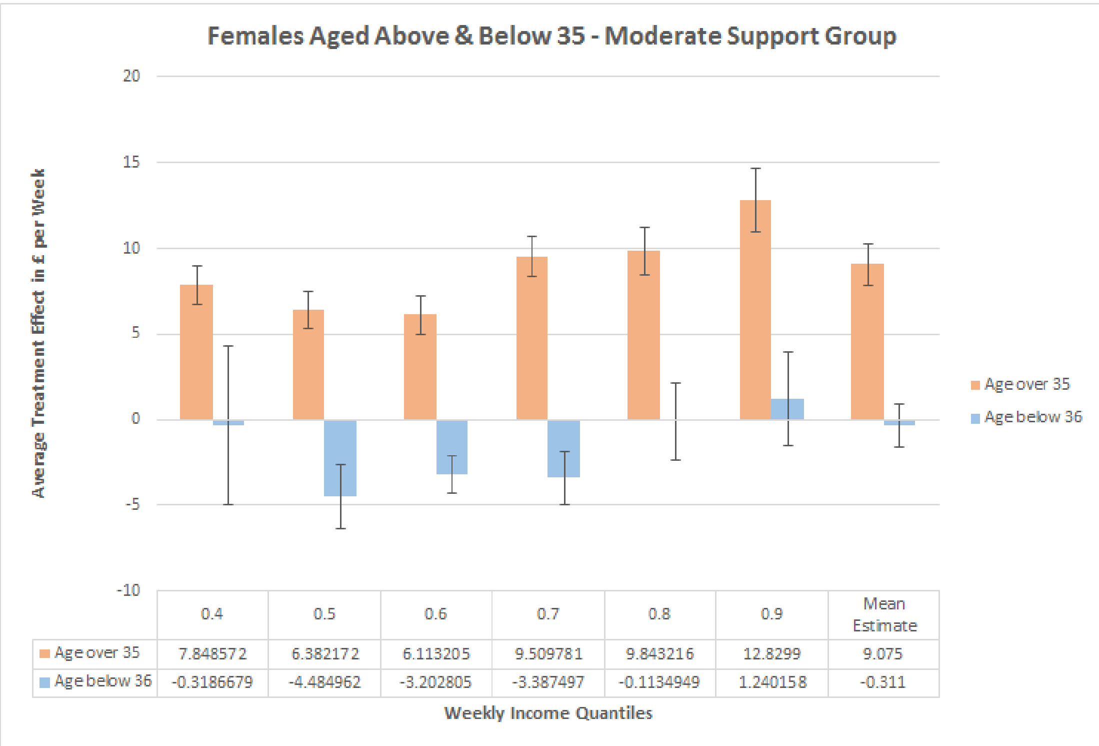
Moderate Support Group

In the case of Moderate support, women over the age of 35 had positive and significant IWP treatment effects throughout the income quantiles investigated as well as at the mean estimate. The results show a generally increasing trend for effect sizes at higher quantiles. Further, the estimated effects are also greater in magnitude, showing that the IWP trial was a success for women aged over 35 years.

However, for women below the age of 35, we see significant results at the 0.5, 0.6 and 0.7 quantile where the estimated effects are negative. The estimated effects from Moderate support at the 0.4, 0.8, 0.9 quantiles as well as the mean effect are found to be insignificant for women below the age of 35.

These results which are presented below in Figure 10 highlight a very important difference in the IWP trial outcomes between women above and below the age of 35 under the Moderate support group. Women below the age of 35 faced negative and significant outcomes, while women over the age of 35 had positive and significant progression in their weekly incomes of higher than usual magnitude.

Figure 10: **Females Aged Above & Below 35 - Moderate Support**



Subsequently, we test to see if the above results had statistically significant differences across each of the quantiles estimated. The results, shown as p-values and presented below in Table 27, show that for women over the age of 35 the estimates are significantly different across almost all quantiles. However, in the case of women aged less than 35 we see significant differences between the estimates for the middle and upper quantiles, though these cannot be reliably interpreted as the underlying IWP treatment effects estimated were insignificant at the 0.4, 0.8 and 0.9 quantiles.

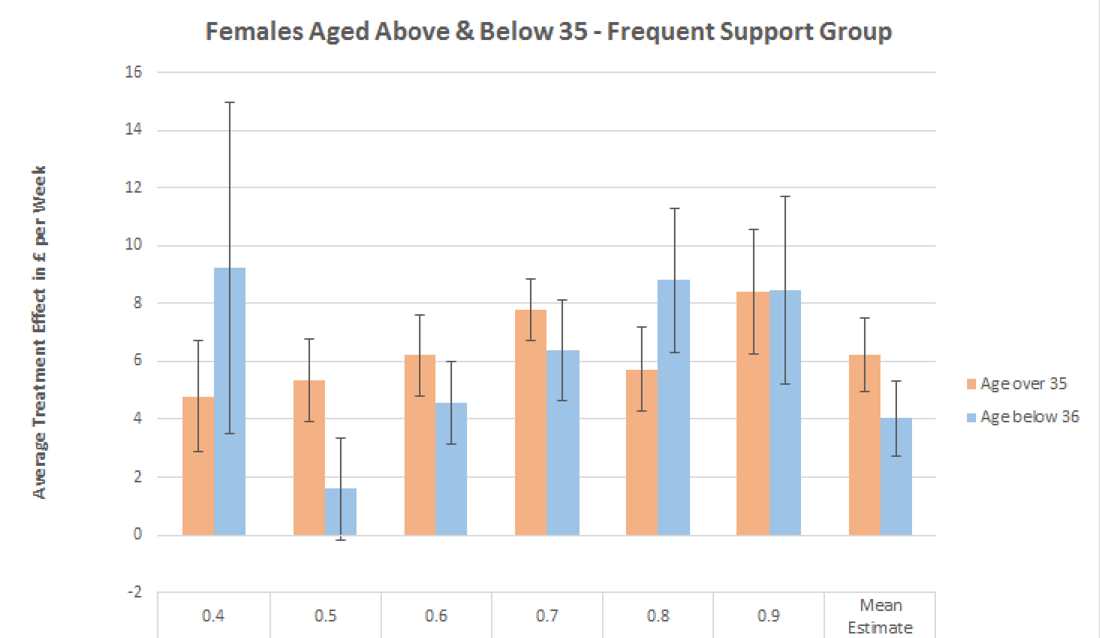
Table 27: **Test for Significant Differences between Estimates - Women Above and Below Age 35 - Moderate Support**

Females over Age 35					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	**0.0005**	**0.0017**	**0.0087**	**0.0146**	**0.0000**
0.5	-	0.4884	**0.0000**	**0.0000**	**0.0000**
0.6		-	**0.0000**	**0.0000**	**0.0000**
0.7			-	0.3514	**0.0000**
0.8				-	**0.0000**
Females below Age 35					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	**0.0120**	0.1624	0.1406	0.9205	0.5572
0.5	-	**0.0471**	0.1705	**0.0000**	**0.0003**
0.6		-	0.7021	**0.0003**	**0.0006**
0.7			-	**0.0000**	**0.0001**
0.8				-	0.1773

Frequent Support Group

The results for women aged above and below 35 years under the Frequent support group are presented in Figure 11 below.

Figure 11: **Females Aged Above & Below 35 - Frequent Support**



	0.4	0.5	0.6	0.7	0.8	0.9	Mean Estimate
Age over 35	4.796959	5.351852	6.209946	7.793594	5.721619	8.395508	6.227
Age below 36	9.230921	1.600021	4.582741	6.403252	8.812622	8.474823	4.026

The investigation for the Frequent support group revealed that women, above and below 35 years of age, had somewhat similar effects from the IWP trial. We see that both cohorts of women had positive and significant results throughout the income quantiles and at the mean estimate. The older cohort of women had higher effect sizes at the 0.5, 0.6, 0.7 quantiles and at the mean estimate, while the younger cohort of women had higher effects sizes in the 0.4, 0.8 and 0.9 income quantiles. The results for older women also demonstrated that income progression increased at higher income quantiles. The same trend of increased effects at higher income quantiles was also true for women below the age of 35, except at the 0.4 quantile, which showed the largest estimated effect with wider than usual standard errors.

Testing to check if the quantile estimates were significantly different to each other revealed that both cohorts of women under Frequent support had significant differences between lower and higher income quantiles. These results, shown as p-values, are presented in Table 28 below.

Table 28: **Test for Significant Differences between Estimates - Women Above and Below Age 35 - Frequent Support**

Females Aged over 35					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	0.1797	**0.0211**	**0.0000**	0.3675	**0.0039**
0.5	-	**0.0358**	**0.0000**	0.6600	**0.0097**
0.6		-	**0.0000**	0.4442	**0.0379**
0.7			-	**0.0001**	0.5097
0.8				-	**0.0002**
Females Aged below 35					
Quantiles	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.4	**0.0008**	**0.0655**	0.2585	0.8776	0.7940
0.5	-	**0.0000**	**0.0000**	**0.0000**	**0.0000**
0.6		-	**0.0001**	**0.0000**	**0.0114**
0.7			-	**0.0010**	0.1483
0.8				-	0.7746

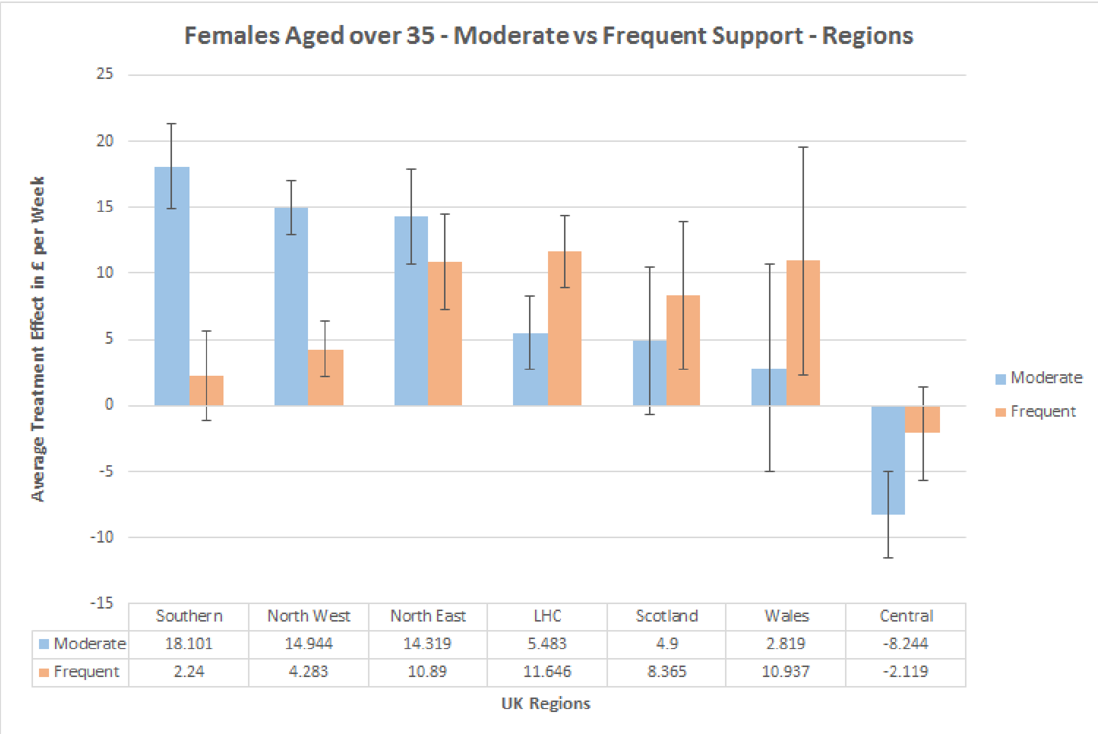
Regions

We also investigate the treatment effects in the case of women aged above 35 to see if there are significant variations across different regions in the UK for Moderate and Frequent support groups. Overall, the results shown in Figure 12 below indicate that the treatment effects realised were positive and significant outcomes in the Southern, North West, North

East, London (LHC) and Scotland regions for Moderate support. However, the Central region saw a significant negative treatment effect and the estimated effect in Wales was insignificant.

For the Frequent support group, we see positive and significant effects for London (LHC), Wales, North East, Scotland and North West. While, the effects are not significant for Southern and Central regions.

Figure 12: **Moderate vs Frequent Treatment for Women over 35 - Regions**



Live-Service vs Full-Service

The investigation of IWP treatment effects between women aged above and below 35 years of age across Live-service and Full-service claimants revealed some interesting results.

Notably, for Moderate support the effects for women aged over 35 years are significant and positive for both Live-service and Full-service claimants. In the case of women less than 35 years of age the estimated treatment effects are negative for both Live-service and Full-service claimants. However, this estimate is significant only for Full-service claimants at the 10% level. For the Frequent support group, we see significant and positive effects for both cohorts of older and younger women. These are presented below in Table 29.

Table 29: **Females Above & Below Age 35 - Live-Service vs Full-Service**

Moderate Support				
	Live-Service	**Std Err**	**P>|t|**	**No of Observations**
Above Age 35	7.033	0.801	0.000	532610
Below Age 36	-0.205	0.744	0.783	445250
	Full-Service	**Std Err**	**P>|t|**	**No of Observations**
Above Age 35	10.91	0.937	0.000	427960
Below Age 36	-2.011	1.177	0.088	210730
Frequent Support				
	Live-Service	**Std Err**	**P>|t|**	**No of Observations**
Above Age 35	6.422	0.827	0.000	512070
Below Age 36	2.617	0.748	0.000	447070
	Full-Service	**Std Err**	**P>|t|**	**No of Observations**
Above Age 35	4.928	0.95	0.000	408330
Below Age 36	5.032	1.205	0.000	209040

Overall, the results show that women had higher income progression compared to men through participation in the IWP trial. Specifically, women over the age of 35 had the best outcomes and generally achieved higher income progression compared to younger women, across Live-service and Full-service groups as well as for both Moderate and Frequent support groups.

3.5 Conclusions

The present research brings out some interesting findings through further investigation of the In-Work Progression trials conducted by the DWP. The randomised dataset was well balanced and suitable for the in-depth analysis of treatment effects conducted in this chapter. Building upon the existing research base of the DWP, the research highlights some aspects that need to be kept in mind while designing further trials based on IWP. Notably, these include the presence of non-earners in the pre-trial period that may bias estimations of the treatment effects upwards. As Smith (2000) highlights, the reliability of ALMP evaluations are paramount to ensure that optimal policy decisions about program expansion and termination are being made.

Overall, the results show considerable differences between the mean estimates and the investigated income quantiles for both Moderate support as well as Frequent support groups. This is in line with Bitler et al. (2006) and Bitler et al. (2008) which noted that ALMP impacts often contain considerable heterogeneity beyond the conventional mean estimates. More specifically, in the case of the Connecticut's Jobs First Waiver the results showed that, *the positive shift in the income distribution occurs at above-median quantiles* (Bitler et al., 2006, p1008). Similarly, in the evaluation of the Canadian Self Sufficiency Project, it was seen that *positive impacts on the income distribution are concentrated in the upper end of the income distribution* (Bitler et al., 2008, p764).

While we find generally positive impacts on both the mean estimates as well as the investigated income quantiles of the claimants, there is an observed larger treatment effect for those claimants already at higher quantiles of the wage distribution. Thus, claimants who are relatively better off in terms of earnings are likely to perform better in the trial. These results are also largely in line with Pacheco et al. (2020) where low-pay workers face lower transition probabilities between low and high pay as well as face a greater risk of falling into no-pay labour market outcomes. This implies that there needs to be a rethink on how the lowest income earners in the trial may better benefit from IWP or similar ALMPs in the future.

Further we see that specific cohorts of claimants have a wide degree of variation in the estimated treatment effects. The majority of the results are estimated at high levels of significance, and these are summarised below. These findings have implications in the larger context for Labour Market Policy in the UK.

Similar to the results noted by Bergemann and Van Den Berg (2008), the impacts from ALMPs seems to have benefited women more than men. In the case of the IWP trial, we see that women tend to have better outcomes while on Moderate support and much better outcomes while on Frequent support. Most notably, men are found to have a significant negative treatment effects while on the Frequent support group.

Claimants on the trial belonged to both Live-service as well as Full-service and the results varied significantly depending on whether they were assigned to Moderate or Frequent support. In the case of Moderate support, Full-service claimants saw exceptionally high levels of treatment effects with substantially increased incomes. However, Live-service claimants on Moderate support saw negative impacts on their wages. In the case of Frequent support, the treatment effects were generally positive, but Live-service claimants mostly outperformed Full-service claimants.

The distribution of IWP treatment impacts by age reveals that Moderate support has a generally positive impact that increases with age. Frequent support was seen to have a rapidly declining impact for those above ages of 46 and a negative impact when claimants were over 56 years of age. Notably, both Moderate and Frequent support had non-significant results for the particular age cohort of 26 to 35 years of age.

The regional variation of treatment effects showed that Wales has the highest recorded treatment effects for both Moderate and Frequent support with North West also performing well for both treatment groups. There could potentially be some valuable lessons related to actual delivery of the IWP interventions by work coaches in these regions that deserve a closer look. Additionally, Central region recorded significant and negative treatment effects in the case of Frequent as well as Moderate support groups.

The key findings of the research were further investigated to ascertain the main driver of the results and it was seen that women aged over 35 are the main beneficiaries with the highest positive treatment effects from the IWP trial. Within this sub-group of claimants as well, those at higher levels of the weekly earnings distribution were seen to progress more through participation in the IWP trial. This is an important factor to keep in mind while designing future labour market policies.

A theoretical framework to explain these results can be structured around a utility maximization model, subject to constraints. We can visualize the IWP claimants at different part of the income distribution in terms of distance to the labour market. The dataset provided contained weekly aggregate earnings for all claimants but did not have information on number of hours worked or earnings per hour of the claimants. Claimants at different parts of the income distribution are likely to have varying circumstances with notable differences in incentives and ability to engage with the labour market. Claimants at higher quantiles of the weekly earnings distribution are closer to the labour market compared to those at the lower end of the income distribution. Generally, claimants at the lower quantiles can be regarded as having limited labour market participation. Higher quantiles, by virtue of having more participation in the labour market, are likely to be able to progress more and benefit more from the trial support offering.

The heterogeneity in results seen between sub-groups of claimants based on gender, age and geographical location can especially be rationalised based on the different incentives and circumstances facing each group. Men and women are likely to have very different reasons to engage with the labour market and these differences are likely further compounded by age of the claimant. Geographical location, which is also likely to be a proxy for employment opportunities, are also most certainly going to have an impact on how claimants respond to labour market changes and IWP participation requirements. As we have seen from the results, women over the ages of 35 were seen to have the highest progression in their incomes from participation in the IWP trial. A possible explanation for this result was that, specifically this sub-group having less childcare obligations and more time for work were able to benefit more from the IWP support offering.

3.5.1 Future Research

Conducting a nationwide Randomised Control Trial is not without cost. Scarce public resources are devoted to this effort and optimising the program for higher efficiency is vital. In this regard, more research on the temporal distribution of the treatment effects can prove to be beneficial to labour market policy design in the future. While the current dataset investigated income progression 52 weeks prior to the trial and 78 weeks after commencement of the trial, there could be potentially interesting learnings to be gained from investigating if the treatment effects are higher at earlier periods after start of the IWP trial or towards later periods after start of the trial. With a longer dataset, another question of relevance is how long will these observed effects last? Further, if more data on the actual duration of the trial interventions are made available, future research could investigate into what ought to be an ideal duration of the ALMP in-order to achieve a good balance with the implementation costs? These may shed light on the recommended duration of future trials.

Finally as noted earlier, regional variations in the treatment effects across the UK imply that the method of administration of the trials while designed to be as uniform as possible could have faced variations due to local factors. These are potentially useful to study as there could be some best practices explaining why some regions consistently managed to outperform others.

4 Investigation of Treatment Effects over Time for In-Work Progression

4.1 Introduction

With the implementation of Universal Credit (UC) in the UK, the DWP has been taking on a larger role in directly helping claimants stay employed and achieve higher earnings. Once UC is fully rolled out, an expected total of seven million households will be among the beneficiaries, with three million of them expected to be in work and about a million under the in-work conditionality regime DWP (2018a). The primary objective of the IWP trial was to test if DWP could help low income workers on Universal Credit to increase their earnings through a mix of support and conditionality.

The IWP Randomised Controlled Trial which ran from April 2015 to March 2018 in stages across the UK was a large undertaking in terms of scale. As seen from the dataset investigated, the trial overtime involved the participation of over 685 Jobcentres, 2000 work coaches and 30,000 claimants. The overall cost of the trial over 3 years of implementation involved direct costs of administering the intervention via Jobcentres as well as indirect costs of organisational resources devoted to monitoring the implementation of the trial. Further, the administration of the trial, at a nationwide scale, understandably involves a degree of heterogeneity in its implementation due to local factors. These involve expected differences in implementation of local ALMPs and a degree of variation in regional practices.

Additionally, there were also potential standardization challenges related to the actual delivery of the IWP trial at Jobcentres across the UK as noted in (DWP, 2018a, p24-25). The creation of Integrity and Operational Support Manager (IOSM) roles for monitoring compliance of the RCT was undertaken to address this specifically. However, a degree of variation existed in the level of training that work coaches received from IOSMs and the DWP for implementing the IWP trial. Further, the nature of the actual intervention during work search reviews also differed. Some work coaches were confident about having meaningful conversations with claimants about their career aspirations while others preferred to provide a basic level of support until they had gained more practical experience with implementing the trial (DWP, 2018a, p26). Finally, the IWP trial saw claimants starting treatment over a relatively long period of time from 2015 to 2017 and these create some challenges for accurate causal estimation of treatment effects and subsequent policy recommendations.

Previously DWP (2019) has also undertaken an aggregated cost benefit analysis to investigate if the earnings impacts seen from the IWP trial exceed the cost of delivery. The DWP publication estimated the *Benefit Cost Ratio* of Moderate support and Frequent support groups at 52 weeks as 7.8 and 2.3 respectively. A benefit cost ratio above 1 implies that the ALMP was *good value-for-money* (DWP, 2019, p4). Notably, the research finds that the benefit cost ratio associated with Moderate support were higher than those observed for the Frequent support group as a result of the higher costs and relative benefits associated with higher frequency of work search reviews.

This chapter builds on the work in the previous chapter and existing DWP research to investigate how the treatment effects are spread over the period of 18 months after entry into the trial. In particular, we investigate the treatment effects over time for Moderate Support as well as Frequent Support groups, and check for possible heterogeneity in the results across sub-samples of men and women, Live-service and Full-service claimants. Subsequently, we look for evidence of a slowdown in increased earnings within the observation period of 18 months. This may indicate if IWP treatment effects tend to peak after a certain period of time, post the start of the trial. We also compare treatment effects between claimants entering the trial in 2015, 2016 and 2017 to check for possible calendar effects.

This has policy relevance to the question of how long the effects of increased earnings from IWP is sustained while keeping in mind the objective to achieve a good balance between the treatment effects observed versus the costs of administering the treatment.

4.1.1 Background and Motivation

Various research has been conducted to assess the treatment impacts over time from ALMPs. This research seeks to add important learnings to the established base of published literature on ALMP evaluation. We build upon the research in the previous chapter using the same DWP administrative dataset with Real Time Earnings Information access to HMRC earnings data to investigate the effectiveness of the IWP trial over time.

The current dataset incorporates claimant earnings data 52 weeks prior to the trial and 78 weeks after commencement of the trial. There could be potentially interesting insights to be gained from investigating how treatment effects evolved after start of the trial. We keep the 78 week (18 month) period after entry into the trial as the observation period of interest and specifically investigate if participants on the IWP trial had higher income progression at earlier or later stages of the observation period.

The methodology for the research proposed involves a difference in difference method that is structurally similar to the one used in the previous chapter. However, a segmentation by duration of the dataset using mutually exclusive time dummies is utilised to be able to differentiate incremental periods of 3 months, after entry into the trial. The treatment effects of the IWP trial over time are first considered for both Moderate support as well as the Frequent support groups relative to the Minimal support group that serves as the comparison group. The methodology used is also applied for an assessment of the treatment effects over time between male and female as well as Live-service and Full-service claimants.

The research also investigates for possible variations in treatment effects between claimants entering the trial in 2015, 2016 and 2017. Differences in treatment effects between claimants based on year of entry into the trial suggest the possible existence of calendar effects. Though, an improvement in estimated effects for claimants entering in later years may also be indicative that the administration of the trial has had a feedback loop back to the work coaches and improved the delivery of the interventions.

This line of investigation adds important understandings to the DWP evidence base. The IWP trial was a national level ALMP in the UK with significant costs of implementation over 3 years. Insights into the treatment effects witnessed over time help shape policy vis a vis the costs of continuing the trial. Thereby proving beneficial for lessons learnt and future policy design.

4.1.2 Research Objectives

This chapter investigates the following research questions.

- **Research Question 1:** Are there significant differences in treatment effects over time between Moderate support and Frequent support groups during the 18 month observation period?

- **Research Question 2:** How do the IWP treatment effects evolve over the observation period for claimants in Moderate & Frequent support groups? Do these vary significantly across the sub-samples of men and women and Live-service vs Full-service claimants?

- **Research Question 3:** Is there evidence of a tapering off in the income progression results seen from the IWP trial after a certain period?

- **Research Question 4:** How do treatment effects for claimants entering the IWP trial at a later year compare to those that started in an earlier year?

4.2 Review of Literature

This section covers the relevant literature reviewed related to Active Labour Market Policy evaluation with a focus on papers that used administrative datasets. The IWP trial had multiple treatment arms within the same ALMP and the treatment administered to participants was of an unknown duration. Previous research that estimated treatment effects over time, duration effects and considered timing differences in administration of the interventions form the core area of interest. Evaluation of an ALMP with multiple treatment arms differs from the evaluation of multiple ALMPs, as a common control group is often used within a single study in the case of the former. Therefore, previous research that conducts an investigation of ALMPs having multiple treatment arms and papers which evaluated ALMPs having structural and methodological relevance to the present research are also selected for the literature review. These are elaborated below.

4.2.1 ALMP Evaluations over Time

Lechner et al. (2011) conduct an analysis of government sponsored training programs in West Germany over an eight-year period to estimate short, medium and long term-effects on employment, unemployment and earnings. The authors use a nonparametric matching estimator, allowing for unrestricted effect heterogeneity, that accounts for multiple treatments as proposed by Imbens (2000) and apply a weighted regression to improve propensity score matching quality. The paper combines various administrative datasets to create a 25-year period of monthly individual employment history with detailed personal, employer and earnings information that allow controlling for many of the factors determining selection into the programs. The results show that short-run effects on employment for all types of training are initially negative with the extent and duration of these effects directly related to the program's duration. While shorter training programs start to show positive effects relatively quickly, the longer duration training programs appear to take even 3 years to show positive effects. However, in the long run all programs increase employment rates and earnings. One of the key findings in the study is that positive effects materialize much earlier for shorter than longer programs.

Flores-Lagunes et al. (2007) deviate from traditional labour market policy evaluation studies that primarily focus on treatment effects between treated and control groups and propose an evaluation method for estimation of treatment effects based on length of the treatment received. Conventional estimators often fail to capture the heterogeneity in effects due to the varying lengths of treatment provided. The study analyses data from the Job Corps, which is the largest training program for disadvantaged youth in USA.

The methodology uses a generalized propensity score estimator under the assumption that length of exposure to the training is random and conditional on observable covariates. The paper estimates average causal effects from varying lengths of the treatment with a dose-response function that is the average effect of the continuous treatment on weekly earnings. Notably, the estimated marginal effect for an additional week of training decline with length of the training. Finally, ethnic differences among participants are also found to be significant with Hispanics showing higher and more long-lasting effects compared to Blacks and Whites.

Crépon et al. (2009) highlight that most ALMPs do not start the administration of the treatment immediately upon individual entry into unemployment, but often after some delay. The reasons for the delayed entry into the program could be several, including administrative reasons, case worker induced or even random. Therefore, the authors propose a methodology to estimate treatment effects when the actual treatment may occur at any point after the start of the program. The identification of the effects in such a dynamic setting wherein non-treated may be treated at a later stage relies on the assumptions of non-anticipation and conditional independence between duration until treatment and the counterfactual durations until exit. The authors use monthly administrative unemployment data from France between 2002 to 2007 which also allows for controlling on typically relevant covariates. At a given date, those unemployed and entering treatment comprise the treatment group and the potential control group comprises those unemployed but not yet given the treatment. Using propensity score matching, the average treatment effect on the treated are estimated. The empirical results show that training investigated did not have much impact on unemployment duration but note that results could vary significantly with dynamic matching as used in the paper and standard matching approaches.

Vikstrom (2017) use 2003-2006 data from the Swedish Public Employment Service to estimate effects from two active labour programs under the possibility of dynamic treatment assignment. Thus, when treatment may start at any time after entry into unemployment, where those currently not being treated may be given treatment at a later date. The paper analyses the impacts from two different labour market programs. Namely, the work practice program for a period of 6 months which provides long-term unemployed individuals practical experience to improve work productivity and a training program which aims to build skills for unemployed individuals in order to increase their probability of gaining employment. Under a discrete time setting the paper uses a dynamic inverse probability weighting estimator to investigate impacts from both programs individually as well as in a sequence. The average treatment effect on the treated against non-treatment in the same period is estimated with the survival time in unemployment as the variable of interest.

The results show that enrolment into the work practice program while facing significant lock-in effects in the initial months does increase employment rates after about 15 months. However, sequences of the different training programs are found to be largely ineffective.

Hujer and Thomsen (2010) use administrative data from Germany to analyse the effects from a job creation scheme by considering the timing of the treatment during the period of unemployment. Programmes that focus on job creation have been an important part of German ALMP with significant public expenditures to support them. However, criticism exists that they fail to create additional human capital to improve the chances of productive employment as well as generate locking-in effects due to long scheme durations and the high wages create negative incentives towards future job search. Specifically, the paper investigates if duration of unemployment at the point of entry into the programme has varying impacts on the chances of re-employment. The effects of the ALMP are estimated separately for different unemployment durations of upto eight quarters prior to the treatment. The methodology incorporates use of propensity score matching to generate a comparison group and estimate average treatment effects on the treated. The results are presented separately for West Germany and East Germany. In West Germany, those joining earlier perform worse and for most groups the treatment effects estimated are insignificant, except for those joining the scheme in the 5th quarter of unemployment. In East Germany the tested groups show negative effects highlighting that participation in the job creation scheme decreases the employment chances at the end of the observation period. The main finding is that the ALMP seems to suffer from strong locking-in effects where future employment search is disincentivised, though negative selection effects cannot be ruled out as ALMPs generally target worse off labour market participants.

Fitzenberger and Volter (2007) analyse three different training programs in East Germany using administrative datasets to estimate their differential effects on quarterly employment rates and benefit recipiency rates. The study uses a dynamic multiple treatment estimator with matching based on entry to unemployment. The treatments investigated include Practice Firms (provision of general skills), Specific Professional Skills and Techniques (providing specific additional skills such as computer skills) and Retraining (mainly vocational training). The methodology differentiates between treatments starting by quarterly increments and analyse the effects of participation in each training program conditional on the start date of the treatment. The results show positive medium and long-term effects on employment for Specific Professional Skills and Techniques. Additionally, all the training programs show increased benefit recipiency rates in the short run as noted via lock in effects. While, none of the training programs are found to reduce the benefit recipiency rates in the medium and long term. The results are found to hold similarly for men and women. Finally, the authors caution that the paper does not address the possible general equilibrium effects from the trainings implemented.

Abbring and Van Den Berg (2003) provides a potential outcomes framework for causal inference in duration models. The paper highlights specification and identification methods of treatment effects when investigating dynamically assigned binary treatment and the variable of interest is an outcome duration. The methodology builds upon the assumption of no-anticipation (where participants do not have any information on future treatment), and the assumption of randomised treatment assignment without restriction of observational data. To address possible selection effects, the paper explicitly models the effects of observed and unobserved covariates on outcomes and assignment. The authors examine both single-spell and multiple-spell settings where the treatment effects can be identified and estimated. Overall, the examination of the relationship between the outcome duration and treatment time highlights the importance of the timing of events on the treatment effects.

Heckman and Navarro (2007) move beyond the conventional static models of estimating treatment effects and present identification strategies for models with structural dynamic discrete choice and dynamic treatment effects with potentially multiple systems of outcomes. By analysing the timing of treatments and treatment duration choices, the authors present semiparametric identification strategies. The models build upon the assumption of access to panel data with statistically independent observations across individuals, but which may be dependent across time for each individual. The paper develops single spell duration models with general error structures, duration dependence and reduced form dynamic treatment effects with varying assumptions that may suit different econometric problems based on the availability of data and the functional form of the models discussed. Overall, the contribution of the paper is towards the identification and estimation of causal treatment effect models under a dynamic setting.

Vikstrom (2015) investigate further into the fact that 24% of unemployed Swedish labour market participants participate in more than one ALMP as well as participate in the same program more than once during their unemployment spell. The author analyses the effects of sequences of treatments with the duration of unemployment spell being the outcome of interest, provided treatments are administered while participants are unemployed. The methodology involves logit regression models to estimate propensity scores, conditioning on available covariates and the use of inverse probability weighting estimators for the average effects. The assumptions of non-anticipated future treatments and sequential unconfoundedness (conditional on covariates, treatment assignment among the non-treated survivors remains unrelated to future potential outcomes) among those remaining unemployed are required to hold. The dataset used includes unemployed individuals in the Work Practice Program, Training Program and Subsidized Employment Programs offered by the Swedish Public Employment Service. The paper estimates duration outcomes from different combinations and sequences of the three ALMPs to assess whether early enrolment is beneficial to late enrolment, what the effect of spacing between two programs are and whether enrolment in more than one program during the same unemployment spell has beneficial outcomes. The results show that early enrolment is generally more beneficial to later enrolment for labour market outcomes. However, locking-in effects at the start of all ALMPs exist. Further, cases of re-enrolment into the same program or a different program is seen to lead to longer unemployment spells, and this is explained by the additional lock-in effects from the second program.

Lechner and Wiehler (2013) analyse administrative Austrian employment data to evaluate the effects of multiple participation in training programmes. The quantitative evaluation of labour market policies often increase in complexity with different entry triggers at different stages of unemployment for more than one program. This leads to econometric challenges in estimation due to the inherent dynamic selection bias. The authors allow for dynamic selection into various stages of the programs and analyse the timing and order of labour market programs using a dynamic potential outcomes approach. By observing the driving allocation factors in different time periods, the estimation model allows for identification of the potential outcome of a sequence, for non-participants in the said sequence with similar characteristics. This improves understanding of the dynamic selection effects within each sequence. The findings show that active job search programs are more effective after a qualification program as opposed to the reverse order. Further, allocation into job search, qualification and course subsidy programs early in the unemployment spell shows better results for labour market outcomes than later enrolment. The evaluated labour market programs lose effectiveness when started later in the unemployment spell.

4.2.2 Evaluation of ALMPs with Multiple Treatment Arms

Frolich (2004) conduct an in-depth review of identification and estimation strategies used in policy evaluation with a focus on ALMPs with multiple treatment programmes. The identification of average treatment effects under a potential outcomes framework with a detailed discussion of the possible selection bias are provided in the paper. Further, the important methodological assumptions such as the stable unit treatment value assumption (potential outcomes for any individual/unit do not vary with the treatments assigned to other individuals/units) which when violated, through interference or interaction between units, gives rise to general equilibrium effects are also explained from a micro-econometric perspective. The paper goes on to identify nonparametric identification strategies, randomised experimental frameworks and methods to control for confounding variables that influence treatment selection and potential outcomes. While randomisation does avoid many of the potential selection bias and confounding variable issues, there could potentially be challenges including the randomisation bias, substitution bias and drop-out bias. The use of instrumental variables, regression discontinuity design and application of bounds for identification are also discussed in detail. Finally, the paper also discusses estimation strategies with the use of generalized matching estimators, propensity score matching and re-weighting estimators. A point of note is that the evaluation of multiple treatments increases in complexity with a greater number of treatments.

Hotz et al. (2006) estimate further into average differential treatment effects when an ALMP has multiple treatments versus a control group. The paper investigates the impacts of the California Greater Avenues to Independence (GAIN) program that encompassed two training components. Namely, Labour Force Attachment (LFA) training and Human Capital Development (HCD) training. The LFA emphasizes job seeker skills such as interview preparation and immediate assistance to secure job placements, while HCD involves vocational and educational training such as completing diplomas and gaining English language skills. The GAIN program saw welfare recipients in six counties of California being randomly assigned to LFA, HCD or a Control group. The authors propose regression-adjustment methods to control for the heterogeneity in local labour market conditions across counties. With over 9 years of data available, the study manages to test the longer-term effects of the GAIN program and concludes that employment and earnings outcomes from the program have differed between shorter-term effects versus the longer-term effects. While in the initial 3 years, the LFA had stronger positive effects over HCD participants, this effect reverses over the longer run in the case of employment rates. The authors conclude that development of work-related skills to improve human capital and employability is an often-overlooked aspect of ALMP that can have sizable impacts on labour market outcomes in the long run.

4.2.3 Evaluation of ALMPs with Structural and Methodological Relevance

Busk (2016) uses official employment register data from Finland to examine the effect of benefit sanctions on the exit rate from unemployment. The Finnish unemployment benefit system encompasses unemployment insurance and labour market support for out of work individuals who may be sanctioned if requirements of efforts to re-engage with the labour market are not fulfilled. The threat of benefit sanctions is expected to increase job search efforts by the unemployed through a warning effect. Additionally, imposition of the benefit sanction is expected to decrease reservation levels of wages of the unemployed and increase job search efforts from an exclusion of benefits effect. The study uses a timing-of-events model that examines the effects of unemployment benefit sanctions on unemployment duration. The estimation model disentangles and separately examines the selection and causal effects of sanctions on the unemployed under a non-anticipation assumption wherein the date of imposition of the sanction is unanticipated. It was found that the effect of sanctions differs according to the type of benefit received. Sanctions were found to increase the exit rate of unemployment to work among labour market support receivers, while for job seekers receiving unemployment insurance benefits the sanctions were found to encourage them to leave the labour force.

Lechner and Melly (2007) estimate the effects of training programs on earnings capacity as opposed to realized earnings. The paper notes that most studies evaluating the effects of ALMPs fail to consider that such programs are predominantly targeted at individuals with low employment probabilities and the treatment effects estimated are often driven by differences in employment rates. As is often the case, labour market training programs also involve positive selection effects for participation and into employment. The authors set out to assess the treatment effects on human capital or the differences in the distribution of earnings, assuming that the treated and non-treated would have found jobs. The estimation strategy used involves placing bounds on the average and quantile treatment effects with matching. Nonparametric estimators for all bounds are then applied to the ALMP evaluation. The study investigates administrative employment data from 1993-1994 in West Germany and evaluates shorter term training of upto 6 months as well as longer term training programs for over a year. The results show significant increases in earnings capacity of the participants.

Schiprowski (2020) investigates the importance of Caseworkers for ALMP outcomes by evaluating individual level administrative data from Swiss Unemployment Insurance between 2010 to 2012. The author considers unplanned absences of the caseworker as exogenous variations in the quality and quantity of their interactions with the unemployed. The paper evaluates the impact of caseworker meetings and also considers the heterogeneity of the productivity of caseworkers for unemployment duration outcomes and unemployment exit probabilities. Caseworker meetings are obligatory, with benefit sanctions applicable if unemployed individuals do not attend. The results demonstrate that unemployment durations are longer when caseworker meetings are cancelled. An unplanned absence of a single meeting results in increased unemployment duration of about 12 days. Further, when meetings are cancelled but reassigned to another caseworker, there are possible negative spillover effects that affect productivity of the second caseworker due to possible overloading. The methodology also ranks caseworkers based on productivity and finds important distinctions for missed meetings with caseworkers above and below the median rank. The analysis reveals that missed meetings with lower ranked caseworkers result in zero effects overall wherein the loss in the meeting is offset by the higher productivity of new caseworker. However, if the original caseworker is ranked high in productivity and a meeting is missed, the resulting effect on unemployment duration is more than twice the average effect. This shows the inherently low replaceability for productive caseworkers in ALMP administration and that unplanned absences by caseworkers may result in significant economic costs.

Caliendo et al. (2017) conduct an investigation into the importance of unobservable variables while estimating treatment effects in ALMP. Using administrative data from Germany combined with survey data that includes information on usually unobservable individual characteristics such as personality traits, attitudes, expectations, social networks and intergenerational information, the paper evaluates three programs for individuals entering unemployment between June 2007 and May 2008. The effect of short-term trainings with a maximum term of eight weeks, long term trainings with a duration of upto three years, and wage subsidies that reduce labour costs for firms with a view to reduce worker productivity inadequacies are evaluated on labour market outcomes of employment probabilities and cumulative earnings. Almost all nonexperimental methods require unconfoundedness or the conditional independence assumption to hold, failing which unobserved characteristics may simultaneously influence both treatment assignment and the potential outcome. Econometric studies have focused on conditioning on generally observable characteristics in the context of ALMP such as employment history, socio-economic and demographic information. With the use of usually unobservable data, the paper seeks to test if those unobservables may in fact be relevant on the propensity scores, matching quality and estimation of treatment effects. The results show that while the generally unobserved variables have a significant impact on treatment selection, their impact on the treatment effects are not a cause for concern. The authors explain this result by reasoning that since individual unobservable traits are usually time-invariant, they tend to be correlated to the observable individual labour market histories, which effectively captures most of their influence.

4.2.4 Meta-Analysis of ALMPs

Card et al. (2017) undertake an exhaustive meta-analysis of 207 econometric evaluations of ALMPs. The methodology involves classification of the estimates from different studies based on the sign and significance of the results. Subsequently, the authors also model the effect sizes of the estimates where available for studies measuring program effects on the probability of employment. However, both methods lead to identical results as the variations in the sign and significance of estimated impacts are usually dependent on the variation in the estimated effect sizes. Further, comparison of estimates from studies using randomised controlled trials with those using non-experimental approaches do not show significant differences. The research finds some interesting results. Notably, short run impacts (less than a year) from ALMPs are not significantly different to zero, but turn positive in the longer term (over 2 years). There is also evidence to suggest that matching different types of labour market programmes to specific participant groups may be beneficial and ALMPs that focus on human capital accumulation generally result in better outcomes. Average impacts vary considerably across groups with women and long-term unemployed participants likely to have larger gains. Finally, ALMPs seem to work better during times of slow economic growth and higher unemployment.

Vooren et al. (2019) conduct a meta-analysis of 57 ALMP evaluation studies published between 1990 and 2017 with a view to assess their effectiveness. The paper differentiates between short and longer-term impacts from 6 months to 36 months after start of the ALMP and correct for possible publication bias (where publication may depend on the high treatment effects reported) as well as country-specific macroeconomic heterogeneity. Considering possible selection effects and to ensure proper identification of the treatment effects, the authors only review peer reviewed studies that encompass randomised control trials and quasi-experimental studies. The evaluation analysis focuses on four types of ALMPs, namely training programs, subsidized labour schemes, public sector employment schemes and enhanced services schemes. The results show that enhanced service schemes while effective in the short term are not statistically significant in the long term. Subsidized labour schemes and public sector employment schemes face initial lock-in effects where treatment results in negative effects in the shorter-term that turn positive in the longer-term. Job search assistance and training programs were seen to have positive impacts over the medium to longer term, from 6 to 36 months after program start. Overall, the ALMP effect sizes estimated are small highlighting the need for rigorous cost benefit analyses.

4.3 Data and Methodology

The main purpose of this chapter is to investigate how the IWP treatment effects progressed over time, after start of the trial. Keeping in line with this objective, the literature review focused on research publications that evaluated ALMPs with multiple treatment arms, where delivery of the interventions were administered at different points in time, and made use of administrative datasets. As noted by Frolich (2004), the evaluation of ALMPs with multiple treatments often have increased complexity. Relevant methodological aspects for evaluation of ALMPs over time as noted by Lechner et al. (2011), Flores-Lagunes et al. (2007) and Crépon et al. (2009) are also taken into consideration while formulating the empirical strategy. In the present research, we are constrained in the specification of the research model since data on the actual trial duration or timing of the delivery of interventions is not available. However, weekly income data is available after start of the trial for 78 weeks. Therefore, our specification involves investigating how the treatment effects evolved after start of the trial, for each IWP support group. This section describes the dataset and the research methodology used in detail.

4.3.1 Description of the Dataset

This chapter uses the same administrative dataset made available from the DWP servers that was utilised in the previous chapter. Post start of the trial, weekly income data for a total of 78 weeks is available, this equals 18 months of earnings data after entry into the trial. These are categorised into 13 week increments, each representing 3 months of the total 18 month observation period. This allows for further detailed investigations of the IWP treatment effects over time.

4.3.2 Research Methodology

The methodology used for estimation of the treatment effects observed from the IWP Trial over time are described in the following sections. First we generate mutually exclusive time dummies representing 1-3, 4-6, 7-9, 10-12, 13-15 and 16-18 month periods after start of the trial. We then estimate treatment effects from the IWP trial during each mutually exclusive 3 month period to observe how the impact from the trial has evolved after start of the trial. This specification allows for a consistent investigation of whether the impact of the treatment effect varied significantly over the observation period. Through each 3 month increment, we compare to see where along the 18 month observation period claimants had higher treatment effects. Further, we also check if there has been a tapering off in the estimated effects after a certain period of time. These results are also investigated separately for men and women as well as Full-service vs Live-service claimants.

Finally, the research also divides the claimant pool based on year of entry into the trial and investigates the treatment effects. A key point in the design of the trial was that start date of the intervention was spread over 3 years in 2015, 2016 and 2017 and therefore calendar effects between each year may exist. Claimants starting the IWP trial in an earlier year could have significant differences with claimants starting in a later year for various reasons. These may include, among others, differences in the claimant pool, changes to the overall labour market, and a self-reinforcing positive cycle wherein work coaches may gain more experience in administering the intervention, thereby increasing the efficacy of the IWP trial. We divide the claimants from the IWP trial into sub-samples based on the year of entry into the trial and estimate treatment effects for each IWP support group.

The next section elaborates the model specifications used for the research and a full representation of the time dummies used in the regression models are presented in tabulated form for easy reference in Appendix A.3.1.

Estimation of Treatment effects over Time:

The regression model specifications for investigation of the IWP treatment effects over time is as below. In this model, we divide the observation period into 3 month increments (13 weeks) and estimate comparable treatment effects for each 3 month period post the start of the IWP trial. The use of mutually exclusive time dummies as specified below allows for the estimation of the treatment effects in each incremental three month period after start of the trial.

$$Y_{i,t} = \beta_0 + \sum_{i=1}^{6} \beta_i T_i + \gamma_0 IWP + \sum_{i=6}^{6} \gamma_i (T_i * IWP) + \epsilon_{i,t} \tag{10}$$

Where,

- $Y_{i,t}$ is Dependent Variable of Weekly Income.
- IWP is the Treatment Dummy: IWP = 0 for Minimal Support and IWP = 1 for Moderate or Frequent Support Group.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.
- T_1 is Time Dummy. T_1=1 for post-trial period Weeks 53 to 65, Else T_1=0.
- T_2 is Time Dummy. T_2=1 for post-trial period Weeks 66 to 78, Else T_2=0.
- T_3 is Time Dummy. T_3=1 for post-trial period Weeks 79 to 91, Else T_3=0.

- T_4 is Time Dummy. T_4=1 for post-trial period Weeks 92 to 104, Else T_4=0.
- T_5 is Time Dummy. T_5=1 for post-trial period Weeks 105 to 117, Else T_5=0.
- T_6 is Time Dummy. T_6=1 for post-trial period Weeks 118 to 130, Else T_6=0.
- $\epsilon_{i,t}$ is the error term.

We run the above regression specification for both Moderate and Frequent support groups versus the Minimal support group to estimate the differential treatment effects in each 3 month period under investigation. Further, we also run the above regression for sub-samples of men and women as well as Live-service vs Full-service claimants separately.

While the regression specifications in the previous chapter provided mean estimates and quantile estimates of the treatment effects at the end of the observation period of 78 weeks. The regression specification used in this chapter, using mutually exclusive time dummies, allows for a comparison of the IWP effects in each incremental three month period after start of the trial. Essentially, this also allows us to also check if the incremental positive treatment effects from the trial are showing signs of a tapering off after a certain period of time.

Treatment Effects by Trial Start Year:

The dataset contains information about the start date of the trial for each claimant. From this data, year dummies corresponding to the start year for the intervention for each claimant is generated. Claimants entered the trial in 2015, 2016 and 2017. Subsequently, we run the below regression model separately for each sub-sample of claimants based on year of entry into the trial to compare the effects.

$$Y_{i,t} = \beta_0 + \beta_1 T + \beta_2 IWP + \beta_3 (T * IWP) + \epsilon_{i,t} \tag{11}$$

Where,

- $Y_{i,t}$ is the Dependent Variable of Weekly Income.
- T is Time Dummy. T=0 for Pre-Trial and T=1 for Post-Trial Periods.
- IWP is the Treatment Dummy: IWP = 0 for Minimal Support and IWP = 1 for Moderate or Frequent Support Group.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.

- $\epsilon_{i,t}$ is the Error Term.

A closer examination of the dataset based on year of entry into the trial revealed that 2015 claimants represent only about 2% of the total individuals in the dataset as shown below in Table 30.

Table 30: **Summary Statistics for IWP by Year of Trial Entry**

Year	**2015**	**2016**	**2017**	**Total**
Minimal	239	6708	4160	11107
Moderate	191	6281	3905	10377
Frequent	223	6010	3739	9972
Total	653	18999	11804	31456

Therefore, we drop the 2015 claimants and also run a pooled regression to estimate the differential impacts of the trial for individuals entering in 2017 versus 2016. This allows for a much more meaningful comparison of the differences in treatment effects across both years. The regression model used is specified as below.

$$\begin{aligned} Y_{i,t} = \beta_0 + \beta_1 T + \beta_2 IWP + \beta_3 Y_{2017} + \beta_4 (T * IWP) + \beta_5 (T * Y_{2017}) \\ + \beta_6 (IWP * Y_{2017}) + \beta_7 (T * IWP * Y_{2017}) + \epsilon_{i,t} \end{aligned} \tag{12}$$

Where,

- $Y_{i,t}$ is the Dependent Variable of Weekly Income.
- T is Time Dummy. T=0 for Pre-Trial and T=1 for Post-Trial Periods.
- IWP is the Treatment Dummy: IWP = 0 for Minimal Support and IWP = 1 for Moderate or Frequent Support Group.
- Y_{2017} is the Trial Start Year Dummy. Where 2016 = 0 and 2017 = 1.
- $(T * IWP)$ is the Time and IWP Treatment Interaction Term.
- $(T * Y_{2017})$ is the Time and Trial Start Year Interaction Term.
- $(IWP * Y_{2017})$ is the IWP Treatment and Trial Start Year Interaction Term.
- $(T * IWP * Y_{2017})$ is the Triple Interaction Term between Time, IWP Treatment, and Trial Start Year.
- $\epsilon_{i,t}$ is the Error Term.

4.4 Results and Discussion

This section describes the results for the regression models specified in the previous section. We first investigate the differential treatment effects in each 3 month period after entry into the trial for Frequent and Moderate support groups. Subsequently, we consider these effects over time for sub-samples of men and women and Full-service vs Live-service claimants. Further, we engage in a check for the treatment effects based on year of entry in the trial for 2015, 2016 and 2017 separately as sub-samples. Finally, we drop 2015 entrants on account of the low number of individuals in the dataset and compare the results of the 2017 entrants with 2016 entrants as a pooled regression.

4.4.1 Estimation of IWP Treatment Effects over Time.

The regression model used in this chapter involves the dataset being defined into time periods of 3 months after start of the trial. Mutually exclusive time dummies representing 1-3, 4-6, 7-9, 10-12, 13-15 and 16-18 months were generated for the observation period. Since data on the date of interventions as well as actual trial duration is not available, we are constrained to investigate the period after the start of the IWP trial. Thus, with 18 months data representing 78 weeks of weekly earnings data, we define the period of investigation as 6 quarters, commencing immediately after claimants enter the IWP trial.

The results generated allow for the estimation of treatment effects over time. We estimate comparable marginal treatment effects during each 3 month period in the 18 months of data available. Essentially, this forms a comparison of the IWP treatment effects over time, for each quarter, after start of the trial.

The specification enables us to investigate when claimants experienced higher income progression after entry into the trial. The results are generated for the Moderate and Frequent support groups as well as cohorts of men and women and Live-service vs Full-service claimants keeping in line with the research objectives. Subsequently, we also test the estimated effects to see if they are significantly different to each other. The main results for this section are summarised below with the full tabulated results in Appendix A.3.2.

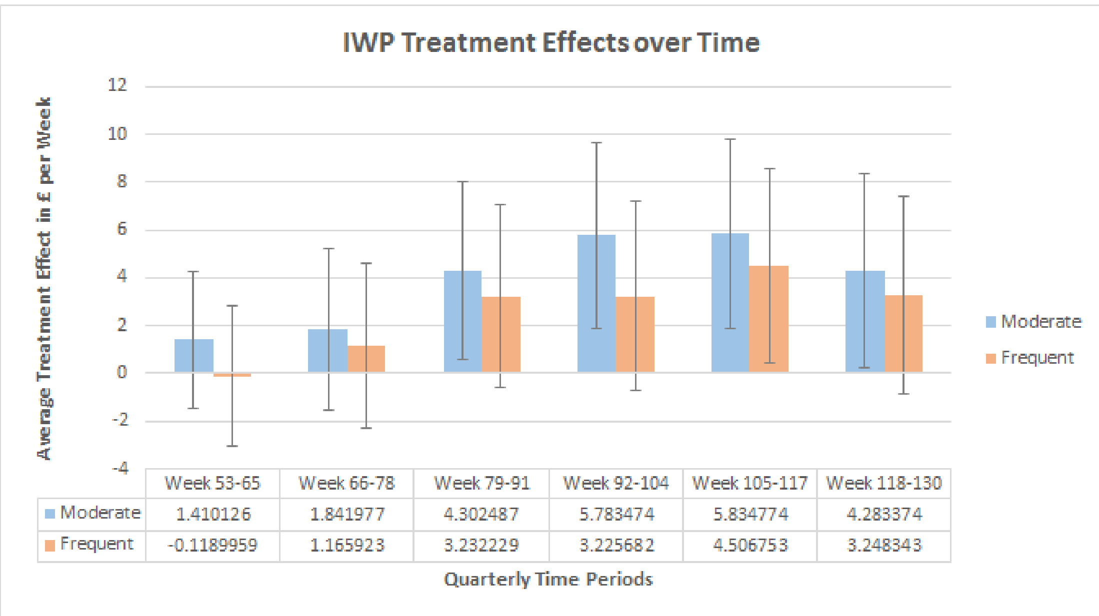
IWP Treatment Effects over Time - Moderate & Frequent Support:

From Figure 13 below we see that the Moderate support group saw significant and positive treatment effects after a period of 6 months from start of the trial. Claimants under Moderate support did not show significant results in the first 6 months. We also see a slight dip in estimated treatment effects after 15 months.

For the Frequent support group, we see insignificant outcomes in the first 6 month period as well as in the period between months 10-12 and 16-18 after start of the trial. Significant treatment effects, which are positive, are observed only in the periods 7-9 and 13-15 months after start of the trial. We also see a drop in estimated treatment effects after 15 months, as was observed with the Moderate support group.

Overall, the results indicate the treatment effects showing an increasing trend that peaks around 12 to 15 months after start of the trial. However, the wide standard error bands for both IWP support groups indicate the high statistical uncertainty associated with these results. Finally, we note that the results are consistent with those of the previous chapter where Moderate support groups had overall better outcomes for claimants in the IWP trial.

Figure 13: **IWP Treatment Effects over Time - Moderate & Frequent Support**



We test both sets of results for statistical differences and see the following result as shown Table 31 below. Where a significant difference is estimated between each of the time periods investigated, we highlight the result in bold. Overall we find that the estimated effects have significant differences between the trial impact seen in earlier months compared to the later months, after entry into the trial.

We see that Moderate support group had significant differences between the treatment effects estimated in the earlier periods versus the later periods. This is evidenced by the significance of the tests between the estimates in the 1-3 and 4-6 month period with the 7-9, 10-12 and 13-15 month periods.

Similarly, in the case of Frequent support we observe that the 1-3 month period shows a significant difference with the 7-9, 10-12, 13-15 and 16-18 month periods. A significant difference between the estimates for the 4-6 and the 13-15 month period is also observed.

Table 31: **Test for Significant Differences between Estimates - Moderate & Frequent Support**

Minimal vs Moderate Support					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.7089	**0.0611**	**0.0108**	**0.0125**	0.1173
4-6	-	**0.0551**	**0.0153**	**0.0220**	0.1730
7-9		-	0.2787	0.3478	0.9912
10-12			-	0.9682	0.3411
13-15				-	0.1992
Minimal vs Frequent Support					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.2872	**0.0339**	**0.0516**	**0.0098**	**0.0695**
4-6	-	0.1161	0.2061	**0.0573**	0.2540
7-9		-	0.9962	0.4407	0.9928
10-12			-	0.3218	0.9886
13-15				-	0.3001

IWP Treatment Effects over Time - Male vs Female:

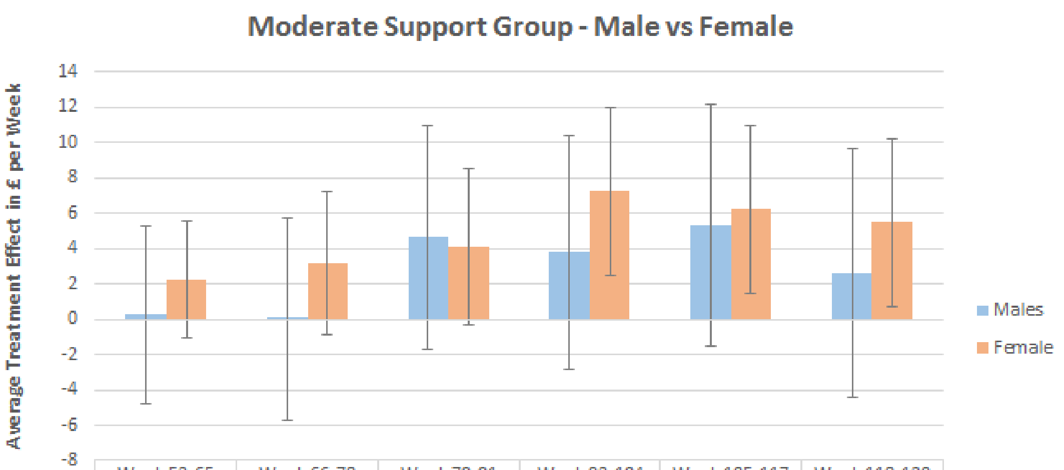
The results for men and women are also compared using the above regression model to estimate the treatment effects seen over time, after start of the IWP trial. The main objective of this was to investigate if men and women had significantly different outcomes over time based on the type of treatment administered. The results are separately summarised for Moderate and Frequent support below.

Moderate Support - Male vs Female

In the case of Moderate support, for women the treatment effects seen in the first 2 periods of 1-3 and 4-6 months are positive but not statistically significant. After the first 6 months, we see consistent positive and significant treatment effects throughout the remaining period of investigation. The effects show an increasing trend over time that peaks in the 10-12 month period and registers a slight drop in the treatment effects for the last 2 periods.

However, in the case of Moderate support for men, although the effects are positive with an overall increasing trend until the 13-15 month period and a subsequent dip in the last period of 16-18 months, the results are not significant throughout all the time periods considered. This highlights a key result from the investigation that was also observed in Chapter 3. The treatment effects for women were far more promising than those observed for men. The results for males and females under Moderate support are presented in Figure 14 below.

Figure 14: **IWP Treatment Effects over Time - Male vs Female - Moderate Support**



	Week 53-65	Week 66-78	Week 79-91	Week 92-104	Week 105-117	Week 118-130
Males	0.2592653	0.0157854	4.626315	3.802824	5.337817	2.65864
Female	2.253586	3.177069	4.075353	7.232786	6.207107	5.479014

We test to see if the above treatment effects are significantly different to each other and the results are presented in Table 32 below. Women on the trial showed significant differences between the treatment effects estimated in the earlier periods versus those estimated for later periods. Specifically, the results in the 1-3 month were found statistically different to those in the 10-12 and 13-15 month periods. As well as the 4-6 and 7-9 month period being significantly different to the 10-12 month period.

In the case of men on Moderate support, we see a significant difference between the 1-3 month period and the 13-15 month period as well as a significant difference between the 4-6 month period with the 7-9 and 13-15 month periods. However, we are unable to interpret these differences reliably as the underlying treatment effects estimated for men under Moderate support was found to be insignificant.

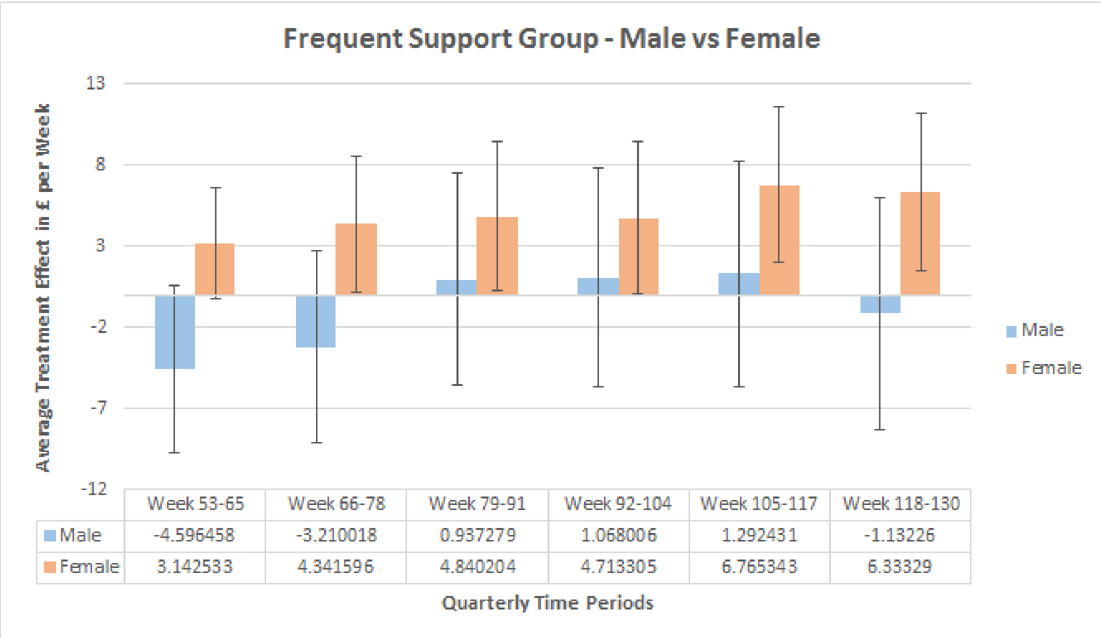
Table 32: **Test for Significant Differences between Estimates - Moderate Support - Male vs Female**

Minimal vs Moderate - Males					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.9027	0.1037	0.2284	**0.0998**	0.4560
4-6	-	**0.0337**	0.1685	**0.0765**	0.3922
7-9		-	0.7196	0.8021	0.5184
10-12			-	0.4811	0.6721
13-15				-	0.2104
Minimal vs Moderate - Females					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.5020	0.3163	**0.0151**	**0.0571**	0.1305
4-6	-	0.5630	**0.0396**	0.1432	0.2789
7-9		-	**0.0588**	0.2667	0.4901
10-12			-	0.5115	0.3511
13-15				-	0.6006

Frequent Support - Male vs Female

The investigation of the treatment effects over time from the Frequent support show a similar overall result between men and women as seen above for Moderate support. These are presented in Figure 15 below.

Figure 15: **IWP Treatment Effects over Time - Male vs Female - Frequent Support**



The results for men are found to be insignificant throughout all the time periods investigated, except in the 1-3 month period where Frequent support was seen to have a negative and significant result for men. This result follows on from Chapter 3 where Frequent support did not show improved outcomes in weekly income for male participants. The main implication of this being that, men may have been less receptive to the frequent level of support in the IWP trial.

For women the effects of Frequent support are much more promising. The results are positive and significant throughout all the time periods investigated. We also see an increasing trend in the treatment effect over time. The increase in earnings attributable to the Frequent support of the IWP trial is seen to reach a maximum point during the 13-15 month period, with a slight dip being observed in the last time period.

As previously done, we also test for statistical differences between these estimates and see the results in Table 33 below.

Table 33: **Test for Significant Differences between Estimates - Frequent Support - Male vs Female**

Minimal vs Frequent - Males					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.4982	**0.0419**	**0.0557**	**0.0554**	0.2836
4-6	-	**0.0614**	0.1229	0.1334	0.5087
7-9		-	0.9557	0.9008	0.5021
10-12			-	0.9199	0.4283
13-15				-	0.2518
Minimal vs Frequent - Females					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.4100	0.3646	0.4403	**0.0888**	0.1412
4-6	-	0.7545	0.8492	0.2490	0.3570
7-9		-	0.9375	0.3252	0.4743
10-12			-	0.1795	0.3746
13-15				-	0.7610

The post estimation checks reveal that women have a significant difference in the estimated effects only between the 1-3 month period and the 13-15 month period. While for men we see a significant difference between the estimates of the 1-3 month period with those of the 7-9, 10-12 and 13-15 month periods. Further, we observe that 4-6 and 7-9 month periods were also found to be statistically different to each other for men. Interestingly, as seen from the previous result, the treatment effects estimated for men under Frequent support were significant and negative in the 1-3 month period. This adds further weight to the possibility that men may not have found participation in the Frequent support group as suitable as women did.

IWP Treatment Effects over Time - Live-Service vs Full-Service:

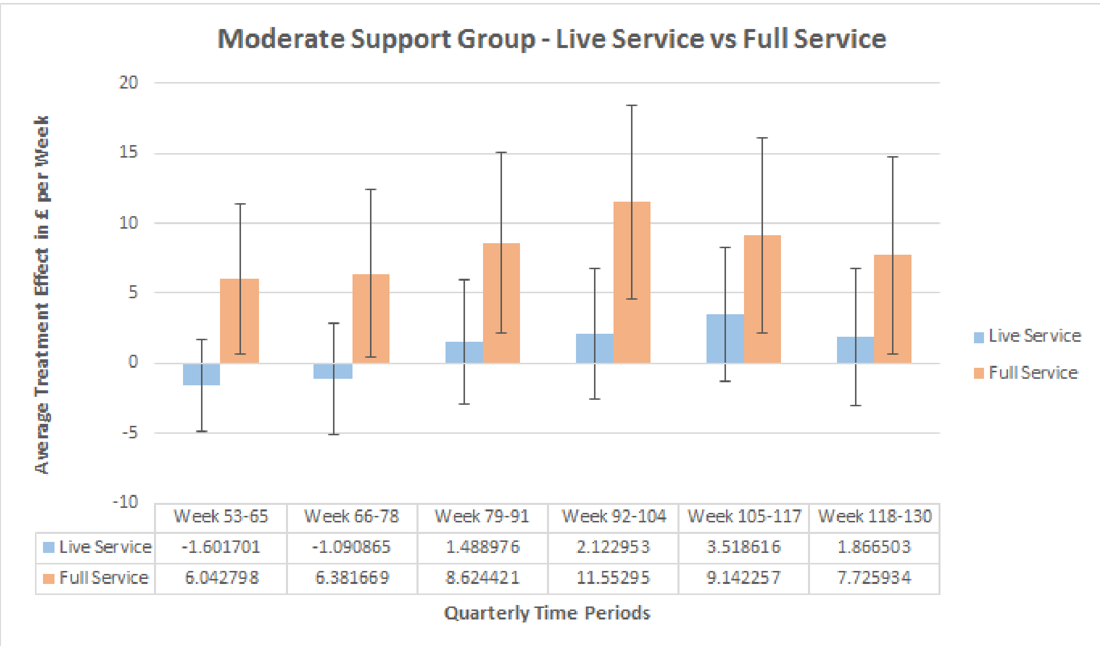
Comparable results for claimants under Live-service and Full-service were also generated to investigate if there was significant differences in treatment effects over time for both levels of support under the IWP trial. These are summarised below for Moderate and Frequent support separately.

Moderate Support - Live-Service vs Full-Service

In the case of Moderate support, Live-service claimants had negative effects in the first 2 time periods and positive effects in the subsequent time periods investigated, however the results are not significant throughout.

We find positive, significant and high treatment effects for Full-service claimants in all the time periods investigated with the maximum effect seen in the 10-12 month period. There is also a clear increasing trend in the effects that peaks towards the end of 12 months and subsequently starts to drop marginally. These results are presented below in Figure 16.

Figure 16: **IWP Treatment Effects over Time - Live-Service vs Full-Service - Moderate Support**



Overall, the results for Live-service and Full-service claimants under Moderate support show significant variation from the IWP trial. Subsequently, we check to see if these estimates are significantly different to each other as shown in Table 34 below.

Table 34: **Test for Significant Differences between Estimates - Moderate Support - Live-Service vs Full-Service**

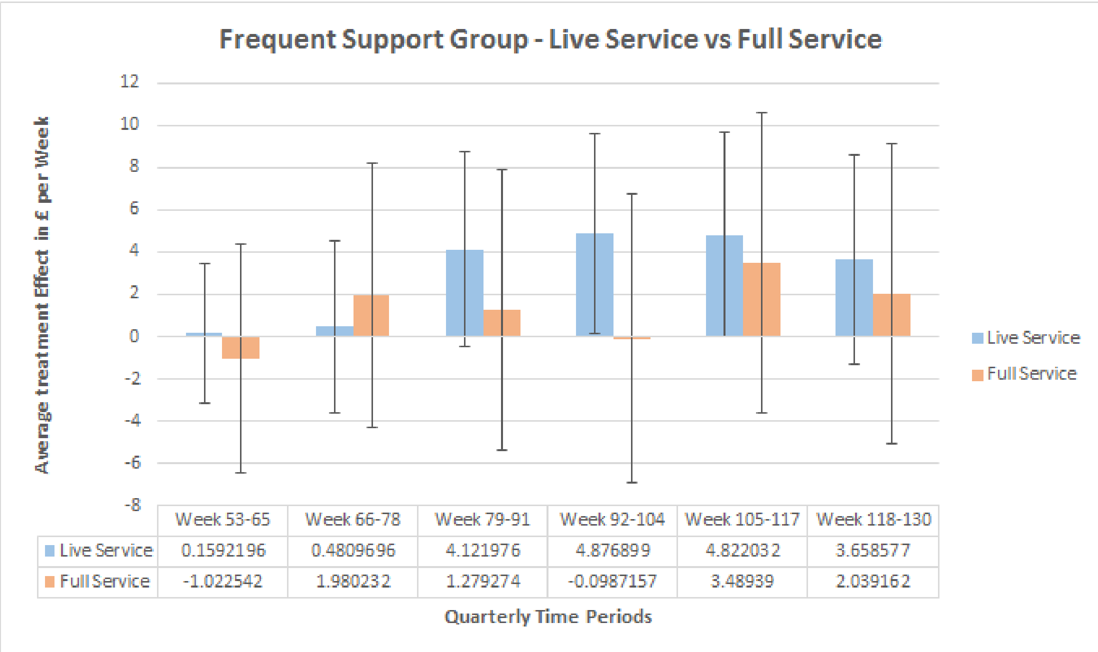
Minimal vs Moderate - Live Service					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.7219	0.1060	**0.0756**	**0.0191**	0.1309
4-6	-	0.1129	0.1108	**0.0342**	0.1922
7-9		-	0.7049	0.3179	0.8629
10-12			-	0.3787	0.8960
13-15				-	0.2770
Minimal vs Moderate - Full Service					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.8623	0.3241	**0.0634**	0.3044	0.5807
4-6	-	0.2822	**0.0601**	0.3425	0.6449
7-9		-	0.2147	0.8500	0.7551
10-12			-	0.2738	0.1479
13-15				-	0.4772

We see that the estimated treatment effects for Live-service claimants in months 1-3 are statistically different to those in months 10-12 and 13-15. We also see a significant difference between months 4-6 and 13-15 for Live-service claimants in the Moderate support group. However, we do not interpret these results due to the underlying effects estimated being insignificant. For Full-service claimants we see that the estimated effects in months 1-3 and 4-6 are significantly different to the effects seen in the 10-12 month period.

Frequent Support - Live-Service vs Full-Service

In the case of Frequent support, we see an almost reverse effect from the IWP trial between Full-service and Live-service claimants as was also noted in Chapter 3. These results which are presented below in Figure 17, show that Full-service claimants have negative effects in the 1-3 and 10-12 month periods and all of the results are not statistically significant throughout the entire period of investigation. However, Live-service claimants have positive effects throughout the investigation period, but the results are only significant for the 7-9, 10-12 and 13-15 month periods. The treatment effects are increasing over time for Live-service claimants, but drop marginally in the last time period between 16-18 months after start of the IWP trial. We also note that the results here have wide standard error bands that signify a large degree of statistical uncertainty in the estimated effects.

Figure 17: **IWP Treatment Effects over Time - Live-Service vs Full-Service - Frequent Support**



Finally, we also test the above results for significant differences between the estimates in each period of investigation and these are presented in Table 35 below.

Table 35: **Test for Significant Differences between Estimates - Frequent Support - Live-Service vs Full-Service**

Minimal vs Frequent - Live Service					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.8278	**0.0452**	**0.0278**	**0.0355**	0.1334
4-6	-	**0.0317**	**0.0325**	**0.0466**	0.1632
7-9		-	0.6627	0.7352	0.8359
10-12			-	0.9724	0.5405
13-15				-	0.4448
Minimal vs Frequent - Full Service					
Month	**4-6**	**7-9**	**10-12**	**13-15**	**16-18**
1-3	0.1486	0.3804	0.7479	0.1363	0.3173
4-6	-	0.7349	0.4356	0.6102	0.9846
7-9		-	0.5340	0.4210	0.7947
10-12			-	0.1057	0.4098
13-15				-	0.4714

From the above results, we see no significant differences between estimates for Full-service claimants under Frequent support throughout the observation period. However, Live-service claimants show the estimates of the 1-3 and 4-6 month periods as being statistically different to the estimated effects in 7-9, 10-12 and 13-15 month periods.

4.4.2 Treatment Effects by Year of Entry into IWP Trial

In the last set of results, we look at the possible heterogeneity in the results as a consequence of the year of starting the trial. Entry into the IWP trial commenced in 2015 and ended in 2017. As a result, the date of inflow of claimants was different for each individual and spread over three years. Further, the trial was implemented in stages throughout the UK and reached a national level of implementation only by December 2015. As noted earlier in Table 30, we see that entry into the trial occurred in 2015, 2016 & 2017. The approximate percentage of claimants entering the trial in each of these years was 2%, 60% and 40% respectively.

Therefore, we keep the year of entry into the trial as a variable of interest for the analysis in this section. However, some caution must be exercised while interpreting the 2015 starters due to the low sample size. The first regression model in this section compares the treatment effects by running a difference in difference estimation of the treatment effects separately for each cohort of claimants based on year of entry into the trial. These results are shown below for Moderate and Frequent support groups in Table 36.

Table 36: **Treatment Effects by Year of Entry into Trial**

Minimal vs Moderate Support				
Year	**Moderate**	**Std Err**	**P>|t|**	**No of Obs**
2015	-1.130628	9.141409	0.902	55900
2016	3.657157	1.923985	0.057	1688570
2017	4.785444	2.593841	0.065	1048450
Minimal vs Frequent Support				
Year	**Frequent**	**Std Err**	**P>|t|**	**No of Obs**
2015	-2.92109	9.228709	0.752	60060
2016	3.525792	1.952986	0.071	1653340
2017	1.247181	2.698601	0.644	1026870

We observe that 2015 starters had negative and insignificant results from the IWP trial for both Frequent and Moderate support groups. The years of interest are 2016 and 2017 and the results show that Moderate support group had significant and positive results in both years, with the 2017 effects marginally higher. The results show that Moderate support group claimants had weekly incomes of £3.65 and £4.78 above the Minimal support group for 2016 and 2017 respectively.

In the case of Frequent support, claimants entering the trial in 2016 had positive and significant results showing an increase in weekly earnings of £3.52 over the Minimal support group. However, for 2017 starters in the Frequent support group, the results were found to be insignificant.

The above results imply that there may be a statistical difference between IWP trial starters in 2016 and 2017. To investigate this further, we drop 2015 starters from the dataset and run a pooled regression to estimate the 2017 treatment effects, keeping 2016 as the base year. These results for both Moderate and Frequent support are shown below in Table 37.

Table 37: **IWP Treatment Effects for 2017 vs 2016 Starters.**

Minimal vs Moderate - 2016 vs 2017			
	Coef	**Std Err**	**P>|t|**
Time	56.7261	1.360727	0.000
IWP Treatment	0.0751401	1.636262	0.963
Trial Start Year	18.27289	1.959806	0.000
Time*IWP	3.657157	1.923958	0.057
Time*Year	-7.619972	2.26895	0.001
IWP*Year	0.0495539	2.80093	0.986
Time*Year*IWP	1.128288	3.229413	0.727
No of Observations - 2737020			
Minimal vs Frequent - 2016 vs 2017			
	Coef	**Std Err**	**P>|t|**
Time	56.7261	1.360727	0.000
IWP Treatment	-0.9093828	1.655642	0.583
Trial Start Year	18.27289	1.959807	0.000
Time*IWP	3.525791	1.952958	0.071
Time*Year	-7.619972	2.268951	0.001
IWP*Year	2.896666	2.917142	0.321
Time*Year*IWP	-2.27861	3.331054	0.494
No of Observations - 2680210			

We see that for both Moderate and Frequent support groups the effects of the treatment is indistinguishable and not significantly different for 2016 and 2017 starters. This leads us to a conclusion that the administration of the IWP trial was fairly consistent over both the years investigated. However, we note that 2017 trial starters had on average £18.2 of higher weekly incomes compared to 2016 starters. This is likely a control for inflation and the economic business cycle movement expected over both years.

4.5 Conclusions

This chapter conducted an evaluation of the treatment effects observed over time from the In-Work Progression Trial that was operational between 2015 to 2017. The research investigated the impact on earnings that participants faced for 18 months after entry into the IWP trial. Mutually exclusive time dummies each representing 3 month periods from the trial start date were generated to estimate the results. This model specification enabled us to get an idea of the marginal impact that participants received in every 3 month period after commencement of the trial.

The main results showed that Moderate support had positive and significant outcomes after the first 6 months with an increasing trend in effects until the 13-15 month period. The final 16-18 month period saw a small decline in treatment effects. These suggest that treatment effects were increasing and then seem to reach a maximum point around a year after the start of the trial. However, for the Frequent support group, while the treatment effects displayed a similar trend of increasing effects until the 13-15 month period, these were only statistically significant in the 7-9 and 13-15 month periods. Overall, the IWP treatment effects were found to be increasing over time, after entry into the trial. This may have partly been a result of work coaches gaining more confidence in administering support under the IWP trial as noted in (DWP, 2018a, p68). Further, claimants on Moderate support generally had better outcomes throughout the observation period compared to those on Frequent support. This is supported by qualitative surveys with work coaches who felt that *'fortnightly meetings may be too frequent for working claimants and experienced a high volume of missed appointments due to changes in working hours'* (DWP, 2018a, p29).

In the case of the present research, we see that the IWP support offered by DWP to low income claimants continued to have positive and significant outcomes for 78 weeks after entry into the trial. The findings highlight that the impact of participation in the Frequent support or Moderate support groups relative to the Minimal support group is sustained till the end of the observation period of 18 months. However, we also note that the estimated impacts in the first 6 months of the IWP trial was not significant. The results are similar to previous findings by Vooren et al. (2019) where meta-analysis of ALMP evaluations showed that job search assistance and training programs were seen to have positive impacts from 6 to 36 months after program start. This is the key finding from the evaluation conducted that highlights the sustained impact of the intervention and shows that the overall impact from the IWP trial continues into the medium to longer term with important policy implications.

The results were then assessed for sub-samples of men and women as well as Live-service and Full-service claimants. In the case of women, we saw generally significant and positive outcomes throughout the period of investigation under Frequent support. For women under Moderate support, the results were positive throughout but significant only after 6 months. Overall, the results were promising for women and seemed to show an increasing trend over time that peaked around 13 to 15 months after start of the trial. Men were observed to have insignificant outcomes for all periods in both Moderate and Frequent support, except for the first 3 months under Frequent support that showed a negative and statistically significant result. These results are largely in line with Bergemann and Van Den Berg (2008) and Card et al. (2017) where women participants on ALMPs had significantly better outcomes compared to men.

The analysis of Full-service claimants displayed positive and significant results in the case of Moderate support with an increasing trend over time that was highest after 12 months. Live-service claimants showed positive and significant earnings outcomes under Frequent support, but statistically significant estimates were seen only after 6 months. We see a similar increasing trend that peaks around 13 to 15 months after start of the trial.

These results highlight the inherent heterogeneity in impacts across different sub-samples and provide the basis for our assessment that the original estimations of the mean effects do not capture all the relevant information. In order to investigate probable reasons for this, more data and research will be needed. Anecdotally, based on interviews with qualified DWP staff, the hypothesis stems from the fact that the trial which is essentially designed as a nudge (Moderate support) towards more labour market participation, may become more of a nag (Frequent support) for men. The data seems to suggest that women are more receptive to the overall trial design and seem to respond better to the regular telephone interviews or meetings.

Finally, the research assessed the likely differences between claimants that started the trial in 2015, 2016 and 2017. It was seen that while 2015 had a very low number of trial starters, the effects were negative and not significant. The 2016 and 2017 pool of starters were investigated in more detail and the results showed no significant difference in treatment effects for claimant earnings between both years. Overall, 2017 entrants into the trial had significantly higher incomes of over £18 per week compared to those that entered the trial in 2016. As noted by the Office for National Statistics, the annual unemployment rate for 2016 and 2017 for the UK was 4.9% and 4.4% respectively[14]. The reduced rate of unemployment in 2017 could potentially have been a causal factor for the calendar effects observed.

4.5.1 Future Research

The most pertinent aspect of the present research that ought to be further investigated is the assessment of longer duration earnings outcomes for claimants in the IWP trial. While the IWP RCT saw a total of 31,501 participants, about 60% of these were starters in 2016. The current dataset provided only 78 weeks of earnings data after start of the treatment. These claimants are ideal for an assessment of the longer term effects on earnings from the trial. The required data for such an examination is available via HMRC Real Time Earnings Information and the DWP Administrative datasets. Official permissions for this research would be the only requirement to undertake an assessment of the effects over 5 years after start of the trial. The analysis of longer term effects may provide further insights into whether such a large scale nationwide ALMP have significant positive effects over a longer horizon as opposed to the immediate short to medium term assessment presently conducted.

Finally, during the course of this research, although efforts were made, no information on the split up of the earnings received by claimants during the observation period was available. There was no way to check if treated individuals were earning more through longer working hours or higher wage rates. In theory, both channels may have an impact on the estimated treatment effects on trial participants. Information related to employer codes and working hours were not available and therefore this could not be checked. This is potentially important as the treatment effects estimated may in fact comprise a degree of substitution and displacement effects, wherein the IWP trial participants have managed to capture more work at the cost of other non-participant workers. The availability of employer codes could also enable investigations to see if income progression was seen in the same job or if IWP trial participants were more likely to shift employment.

[14]https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment /timeseries/mgsx/lms

5 Conclusion

The thesis conducted three distinct, yet related, empirical investigations in the field of labour market economics. In chapter 2, the main focus of the research was to investigate the relationship of mental-health levels with labour market status and labour market transitions. Chapter 3 and 4 conducted a detailed evaluation of a nationwide Active Labour Market Programme in the UK.

In this section, we conclude the thesis with a summary of the findings from each of the three research chapters. Subsequently, some policy recommendations especially with respect to chapter 3 and 4 are provided. Finally, the limitations of the present research and avenues for future research are discussed.

5.1 Summary of Findings

5.1.1 Summary of Findings for Chapter 2

Chapter 2 utilised four fixed-effects regression models to investigate the impact of contemporaneous labour market status and labour market transitions on self reported mental-health levels. The results are similar to existing literature where Schmitz (2011), Kassenboehmer and Haisken-DeNew (2009), Flint et al. (2013) and Thomas et al. (2005) find evidence that the unemployed tend to have poorer levels of mental-health. However, in this chapter we extend the analysis to examine other labour market states and labour market transitions over a much longer period of time.

Model 1A showed that the baseline levels of mental-health associated with employed individuals was better when compared to their unemployed and long-term sick peers. Further, those engaged in family care reported lower levels of mental-health compared to employed individuals. While retired individuals had better self reported levels of mental-health. In Model 1B, we combined employed and self-employed individuals into a single category, but retained unemployed and long-term sick individuals as originally provided in the dataset. Further, we also combined all the remaining categories of retired, maternity leave, family care, students, government training and apprenticeships as economically inactive. Model 1B showed similar results to Model 1A, with unemployed and long-term sick individuals having worse off mental-health scores compared to the base category of employed/self-employed individuals.

Model 2A generated labour market transition variables representing an individual's interaction with the labour market over two consecutive time-periods. The purpose of this was to investigate how mental-health levels associated with labour market transitions. The base category for this regression included individuals who remained in employment or self-employment over both time periods. The impact of a transition between the reference category and unemployment or long-term sickness, showed that transitioning out of employment/self-employment reduced mental-health levels while the reverse movement increased mental-health levels. Though, there is asymmetry in the impacts and higher effect sizes are observed when employment is lost. Finally, we also found that mental-health levels reduced when individuals remained in unemployment or long-term sickness over 2 periods.

Model 2B was similar to model 2A, but had a slightly different specification. We included both the contemporaneous labour market status in the present period as as well as the previous period separately into the regression. This allowed us to see the coefficients for the effects of a labour market transition on mental-health and decompose the results, showing the impact pertaining to the previous time period and for the current period separately. Interestingly, Model 2B shows evidence of partial adaptation where those remaining unemployed are seen to have a smaller negative effect on mental-health, while individuals transitioning from employment/self-employment into unemployment had a larger drop in mental-health levels. A similar result was was also seen between those transitioning from employment/self-employment into long-term sickness and those remaining as long-term sick over the period investigated.

The gender based sub-samples investigated showed that men suffered larger declines in mental-health levels when transitioning from employment into unemployment or long-term sickness. Women enjoyed increased improvements in mental-health levels while gaining employment from unemployment or long-term sickness. Finally, the robustness checks involved use of OLS models to check if the results varied according to the underlying statistical assumptions. Overall, the results were consistent across the different estimators used.

5.1.2 Summary of Findings for Chapter 3

The investigation of the IWP Randomised Controlled Trial in chapter 3 revealed interesting results. Notably, we find significant differences between the conventional mean estimates and with the quantile treatment effects as also noted in Bitler et al. (2006) and Bitler et al. (2008). Claimants with weekly earnings closer to the Conditionality Earnings Threshold, representing higher quantiles on the earnings distribution, have higher treatment effects compared to claimants on lower quantiles. This reveals that the IWP trial has worked better for claimants already in a relatively stronger earnings position.

Comparing the results of participating in the Moderate Support and Frequent support groups between men and women reveal that women had better earnings outcomes for both support groups. This is in line with the results noted in Bergemann and Van Den Berg (2008) and Card et al. (2017). Further, in the case of men on Frequent support, we also saw a negative impact on earnings from the trial. It is of note, that interviews with work coaches revealed their view about Frequent support, which was that the higher frequency of meetings were usually unsuitable for low income claimants already in work, and often prone to missed appointments (DWP, 2018a, p29).

The analysis of Live-service vs Full-service claimants revealed that Moderate support group saw Full-service claimants achieve higher progression at all quantiles investigated, while for the Frequent support group Live-service claimants generally had better outcomes. The investigation of the IWP effects by age cohort revealed that Moderate support worked well with claimants above the age of 45, but Frequent support did not work well with claimants above the age of 45 and had a negative effect for those aged above 55. We also found regional differences in the estimated effects with North West and Wales having consistently higher progression impacts from the trial for both Moderate and Frequent support groups. Finally, the findings also indicated that women over the age of 35 recorded the highest progression in incomes from the IWP trial.

5.1.3 Summary of Findings for Chapter 4

The final research chapter undertook an investigation to see how the IWP treatment effects evolved over time, after entry into the trial. We evaluated a period of 18 months after the start of the trial and found evidence of an increasing trend in the effects over time. Both Moderate and Frequent support groups seemed to have the highest estimated effects at 12-15 months after the start of the trial. However, the results of the Moderate support group were better compared to the Frequent support group.

A similar trend was visible in the case of women which showed the effect of the IWP trial peaking at 12 to 15 months after start of the trial for both Frequent and Moderate support groups. In the case of men though, the results did not hold at a statistically significant level for both support groups. However, for men under Frequent support, a significant negative impact was seen in the first 3 months after start of the trial.

Full-service claimants under Moderate support displayed an increasing trend in income progression over time, which was highest after 12 months from trial start. Live-service claimants under Frequent support also had a similarly increasing trend of higher income progression over time that peaked in the period 12 to 15 months after start of the trial.

The investigation for calendar effects based on year of entry into the trial revealed a significant difference between the average weekly earnings of the 2017 trial starters when compared to 2016 starters, but the IWP trial itself did not have a statistically different effect between both years. This result is likely caused by the difference in the larger macro-economic context of the labour market in the UK between both years.

5.2 Policy Recommendations

The results of chapter 2 revealed that the largest declines in mental-health levels were associated with unemployment and long-term sickness as well as transitioning out of employment into unemployment or long-term sickness. Though the estimated effect sizes are higher for long-term sickness. Traditionally, ALMPs have focused on helping unemployed individuals move into employment. However, policy makers that aim to improve mental-health levels for all labour market participants could succeed by focusing on programmes that help those who are in long-term sickness transition into employment.

Further, the evidence suggests that those remaining in unemployment or long-term sickness may show signs of adaptation with the lag status having a moderating impact on mental-health levels. Therefore, successful ALMPs aiming for improved mental-health outcomes should ideally have short gestation periods.

The IWP trial was conducted nationwide across the UK from 2015 to 2018. Such a large scale ALMP consumes significant organisational resources for the DWP. Thus, optimising the program for higher efficiency is vital. Based on the evidence and present research, the following policy recommendations are made for the improvement of labour market outcomes through similar ALMPs in future.

The impact of the IWP trial was extremely successful for women aged over 35. This reveals a gender difference in how the trial was received. It seems to be the case that women are more receptive to individual case worker meetings with the explicit objective of increasing work and pay. Therefore, future ALMPs of a similar support offering structure may benefit from focusing more on women participants above the ages of 35.

The Frequent support intervention which was delivered fortnightly did not have the expected impacts, especially for men on the trial and for those that were aged over 55 years. Further, we also note that *Case Workers felt that the less intensive treatment regime better fitted the lifestyles of working claimants* (DWP, 2018a, p29).

It is interesting to note that the empirical results confirms the above suggestion made by the work coaches and outcomes for Moderate support were generally better compared to Frequent support. Additionally, as noted by DWP (2018a) success of the trial depended to some extent on the motivation of the claimant and the relationship of claimants with their work coaches. Therefore, the specific policy recommendation for future ALMPs is that work coaches have more flexibility in the administration of the trial interventions. For example; Instead of defining the intervention frequency as every two weeks, defining a band and allowing the work coaches to implement it as best suited for the local situation may be better. Finally, a feedback sharing mechanism between work coaches in different regions across the UK may prove helpful to improve quality of the support interventions.

5.3 Limitations and Future Work

The main limitation of the empirical research in chapter 2 is that we do not arrive at a definitive causal inference of labour market status and labour market transitions on mental-health. This is because of the possibility of selection effects and reverse causality confounding the present results, in the event that the assumption of strict exogeneity is violated. Future research that exploits an exogenous source of unemployment will be needed to arrive at stronger causal estimates of the impact of labour market shocks on mental-health levels. In addition, no investigation was made into the possible impacts that job quality or job security may have on mental-health levels.

Chapter 3 and 4 evaluated the impact of the IWP trial in the UK. One of the limitations in the evaluation was that information on actual delivery of the interventions was not available. The actual frequency of the interventions were subject to cancellations by the claimants. Further, the level of experience of work coaches administering the support varied and this led to differences in the quality of the support offered. These variations are to be expected in a large scale national level ALMP such as the IWP trial, though it does lead to methodological challenges in estimating true causal effects from the IWP trial, especially from a duration point of view. Further, as noted in DWP (2019), the policy regime for Light Touch participants under Universal Credit has changed since the IWP trial.

Investigation of the claimant earnings progression over a longer period of time will be beneficial to bring about more understanding of the longer term impacts of the IWP trial. Specifically, it will shed light on how long the presently observed effects tend to last. Further, if more data on the actual interventions during the trial are made available, future research could investigate into what ought to be an ideal duration of an ALMP such as IWP. This is important to balance the ALMP with its implementation costs.

The differences in the estimated effects over various regions in the UK also highlight that there are potentially important learnings from more research into those regions that had higher income progression to identify possible best practices by the work coaches. This can prove beneficial for better labour market policy design in the future.

Finally, including the employer identification codes from HMRC into the DWP Administrative datasets could prove beneficial to decompose the earnings progression received by claimants on the IWP trial and check if the progression was due to individuals working more hours or earning higher payment rates. It is likely that both channels have contributed to the present results. Future research with employer codes could also enable an investigation into whether IWP trial participants on different levels of support are more likely to change jobs.

A Appendix

A.1 Appendix to Chapter-2

A.1.1 Frequency of Selected Variables across all Waves

Variable Description	BHPS Variable Name	BHPS Variable Code W1	BHPS W1 DTA File	US Variable Name	US Variable Code W1	US W1 DTA FILE	Across BHPS Waves																		Across U.S Waves						
INDIVIDUAL INFORMATION																															
Individual ID	PID	pid	ba_indresp	PIDP	pidp	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Household ID	HID	ba_hid	ba_indresp	HIDP	a_hidp	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Age / YOB	DOBY	ba_doby	ba_indresp	BIRTHY	a_birthy	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Sex	SEX	ba_sex	ba_indresp	SEX	a_sex	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Present Legal Marital Status	MLSTAT	ba_mlstat	ba_indresp	MARSTAT	a_marstat	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Current Labour Force Status / Current Economic Activity	JBSTAT	ba_jbstat	ba_indresp	JBSTAT	a_jbstat	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Highest Education Level	HIQUAL	ba_hiqual_dv	ba_indresp	QF_HIGH	a_qfhigh_dv	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Total Household Income : Last Month	FIMNGRS_DV	ba_fimngrs_dv	ba_indresp	fimngrs_dv	c_fimngrs_dv	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
GENERAL HEALTH / GHQ - MENTAL HEALTH																															
General State of Health	HLSF1 / HLSTAT	ba_hlsf1 / ba_hlstat	ba_indresp	SF1 / SCSF1	a_sf1 / g_scsf1	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
General Health Questionnaire (GHQ)	SCGHQA	ba_scghqa	ba_indresp	SCGHQA	a_scghqa	a_indresp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25

A.1.2 Frequency of Job Status and Labour Market Transition Variables

Frequency of Job Status Variables

Current Job Status	Male	Female	Total
1 Self Employed	22117	10587	32704
2 Employed	108961	124138	233099
3 Unemployed	12417	9488	21905
4 Retired	8561	14833	23394
5 Maternity Leave	9	2485	2494
6 Family Care	1239	28214	29453
7 Full Time Student	14482	17325	31807
8 Long Term Sick / Disabled	8106	8705	16811
9 Govt Training Scheme	441	364	805
10 Unpaid Worker in Family Business	30	113	143
11 Apprenticeship	126	87	213
Total	**176489**	**216339**	**392828**

Frequency of Labour Market Transition Variables

Labour Market Transitions	Male	Female	Total
1 Remains Employed	98413	97818	196231
2 Remains Unemployed	4260	2267	6527
3 Remains Long-term Sick	4914	5012	9926
4 Remains Economically Inactive	12458	36348	48806
5 Unemployed to Employed/Self Employed	3105	2121	5226
6 Unemployed to Long Term Sick	634	487	1121
7 Unemployed to Economically Inactive	897	1871	2768
8 Employed/Self Employed to Unemployed	2487	1827	4314
9 Employed/Self Employed to Long Term Sick	493	557	1050
10 Employed/Self Employed to Economically Inactive	2155	6663	8818
11 Long Term Sick to Employed/Self Employed	274	296	570
12 Long Term Sick to Unemployed	489	395	884
13 Long Term Sick to Economically Inactive	664	1104	1768
14 Economically Inactive to Employed/Self Employed	2727	7927	10654
15 Economically Inactive to Unemployed	1179	2030	3209
16 Economically Inactive to Long Term Sick	508	1005	1513
Total	135657	167728	303385
Missing	40832	48611	89443
Total	**176489**	**216339**	**392828**

A.1.3 Frequency of Control Variables

Frequency of Control Variables

General Health Level	**Male**	**Female**	**Total**
1 Excellent	41541	44476	86017
2 Good	100050	123724	223774
3 Fair	25135	33311	58446
4 Poor	9728	14768	24496
Missing	36	59	95
Total	**176490**	**216338**	**392828**
Marital Status	**Male**	**Female**	**Total**
1 Single	66837	70913	137750
2 Married or Civil Partnership	92765	111525	204290
3 Separated or Divorced	15132	28260	43392
4 Widowed or Surviving Partner	1476	5302	6778
Missing	280	338	618
Total	**176490**	**216338**	**392828**
Highest Education Levels	**Male**	**Female**	**Total**
1 Degree	36563	42972	79535
2 Other Higher Degree	15871	24541	40412
3 A Level	45546	43909	89455
4 GCSE	41140	54920	96060
5 Other Qualification	15784	19844	35628
9 No Qualification	19660	28009	47669
Missing	1926	2143	4069
Total	**176490**	**216338**	**392828**
Number of Children	**Male**	**Female**	**Total**
0	109404	122372	231776
1	29934	42746	72680
2	25882	35343	61225
3	8396	11707	20103
4	1914	2796	4710
5	430	639	1069
6	142	200	342
7	54	68	122
8	14	19	33
9	0	6	6
10	0	3	3
Missing	320	439	759
Total	**176490**	**216338**	**392828**

A.1.4 Hausman Specification Test Results

Hausman Specification Test Results - Model 1A

	FE	RE	Difference	S.E.
SELFEMPLOYED	-0.0380063	-0.1203148	0.0823085	0.0278468
UNEMPLOYED	1.675769	1.776085	-0.1003165	0.0215735
RETIRED	-0.272943	-0.1654406	-0.1075023	0.0313213
MATERNITY_LEAVE	-0.0424877	0.1005143	-0.143002	0.0291846
FAMILY_CARE	0.6287137	0.9052001	-0.2764864	0.0251711
FULLTIME_STUDENT	-0.011972	0.0815508	-0.0935228	0.0335747
LONGTERM_SICK	2.081317	2.728753	-0.6474357	0.0362908
GOVT_TRAINING_SCHEME	-0.0820715	-0.1609842	0.0789127	0.0691535
UNPAID_WORKER	0.155155	0.5982612	-0.4431062	0.1787211
APPRENTICESHIP	-0.11209	-0.5661754	0.4540853	0.1821438
GENERALHEALTH				
Good	0.7484192	1.078842	-0.3304225	0.0106834
Fair	2.191598	2.986342	-0.7947443	0.0155294
Poor	4.807953	6.032474	-1.224522	0.02301
MARSTAT				
Married or Civil Partnership	0.0430915	-0.1504736	0.1935651	0.0382392
Separated or Divorced	0.2673875	0.4935193	-0.2261318	0.0487728
Widowed or Surviving Partner	1.540089	1.151776	0.3883134	0.0999345
EDUCATION				
Other Higher Degree	0.0141979	0.0301448	-0.0159469	0.0957445
A Level	-0.0749912	-0.0054946	-0.0694965	0.067499
GCSE	-0.0724472	-0.0611691	-0.0112781	0.0817275
Other Qualification	-0.0330285	-0.1242342	0.0912057	0.118172
No Qualification	-0.2093977	-0.0646572	-0.1447404	0.1152076
LOG_HH_INCOME_PERCAPITA	-0.1259226	-0.1718221	0.0458995	0.0076252
NUMBER_KIDS	-0.0432111	-0.0621188	0.0189076	0.0110018
ALL_AGE_BANDS				
Aged: 26-35	0.2916159	0.4889471	-0.1973311	0.0337418
Aged: 36-45	0.3990215	0.6889086	-0.2898871	0.0560911
Aged: 46-55	0.2501907	0.5566706	-0.3064799	0.0765267
Aged: 56-65	-0.2383284	-0.1140672	-0.1242612	0.0962218
Year				
1992	0.2223165	0.1744149	0.0479016	0.0144334
1993	0.1817641	0.1116281	0.0701361	0.0165447
1994	0.2681558	0.1895629	0.0785929	0.0182881
1995	0.4171029	0.3300158	0.0870871	0.0200997
1996	0.4118996	0.3072456	0.104654	0.0222206
1997	0.3993797	0.3045047	0.094875	0.0252419
1998	0.3343972	0.2240195	0.1103778	0.0268377
1999	0.4237919	0.3626254	0.0611665	0.0302363
2000	0.4896229	0.3614346	0.1281883	0.0321732
2001	0.4698635	0.3652365	0.104627	0.0350776
2002	0.3758279	0.2573134	0.1185145	0.036834
2003	0.2788447	0.1538899	0.1249548	0.0392857
2004	0.4405062	0.3031272	0.1373789	0.041567
2005	0.5999265	0.4621266	0.1377999	0.0441195
2006	0.5926245	0.4588669	0.1337576	0.0467706
2007	0.5862524	0.4413014	0.1449511	0.0494844
2008	0.8316035	0.649063	0.1825405	0.0524538
2009	-0.072926	0.5346656	-0.6075916	0.1533661
2010	-0.0352784	0.6206319	-0.6559104	0.1512076
2011	-0.0286873	0.64377	-0.6724573	0.1504905
2012	-0.0631858	0.632535	-0.6957207	0.149931
2013	0.1025779	0.7930045	-0.6904267	0.1496151
2014	-0.0889743	0.6097697	-0.698744	0.1493186
2015	-0.1287743	0.570386	-0.6991603	0.1490041
2016	-0.1408737	0.5522796	-0.6931532	0.1483657

Test: Ho: difference in coefficients not systematic
chi2(52) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 3742.58
Prob>chi2 = 0.0000

Hausman Specification Test Results - Model 1B

	FE	RE	Difference	S.E.
UNEMPLOYED	1.645099	1.769994	-0.1248947	0.0212144
LONGTERM_SICK	2.103931	2.756779	-0.6528486	0.0355497
ECONOMICALLY_INACTIVE	0.1438221	0.2992836	-0.1554614	0.0177618
GENERALHEALTH				
Good	0.7495971	1.085368	-0.3357707	0.0106881
Fair	2.194923	3.000934	-0.8060111	0.0155733
Poor	4.806991	6.042332	-1.235341	0.0230761
MARSTAT				
Married or Civil Partnership	0.0693849	-0.1222059	0.1915908	0.038267
Separated or Divorced	0.285937	0.5202709	-0.2343338	0.0487873
Widowed or Surviving Partner	1.497351	1.114359	0.3829918	0.1000608
EDUCATION				
Other Higher Degree	-0.0529038	0.0164342	-0.069338	0.0947506
A Level	-0.1778726	-0.0288125	-0.14906	0.0641662
GCSE	-0.2145826	-0.0723457	-0.1422369	0.0771986
Other Qualification	-0.170631	-0.107623	-0.063008	0.1152071
No Qualification	-0.3697843	-0.047449	-0.3223353	0.1114118
LOG_HH_INCOME_PERCAPITA	-0.1222723	-0.170483	0.0482107	0.0075923
NUMBER_KIDS	-0.0319916	-0.0360549	0.0040633	0.0110397
ALL_AGE_BANDS				
Aged: 26-35	0.3251816	0.5586954	-0.2335138	0.0346333
Aged: 36-45	0.4431212	0.7421884	-0.2990671	0.056446
Aged: 46-55	0.3150549	0.6006801	-0.2856252	0.0764637
Aged: 56-65	-0.2058059	-0.1791677	-0.0266382	0.0972392
Year				
1992	0.2206713	0.1763161	0.0443552	0.0143165
1993	0.1684073	0.1045675	0.0638398	0.0163376
1994	0.2482198	0.1794663	0.0687535	0.0180092
1995	0.3898183	0.3163997	0.0734186	0.0196972
1996	0.3780501	0.2912042	0.0868459	0.0217167
1997	0.3623004	0.2909002	0.0714002	0.0246289
1998	0.2905687	0.208899	0.0816698	0.0261031
1999	0.3720779	0.3399181	0.0321598	0.0294378
2000	0.4318856	0.3367378	0.0951478	0.0312434
2001	0.4059899	0.3398898	0.0661001	0.0340565
2002	0.3078952	0.2321215	0.0757738	0.035682
2003	0.2066259	0.1279299	0.078696	0.0380232
2004	0.3598664	0.2721244	0.0877419	0.0402112
2005	0.5155503	0.4313735	0.0841768	0.0426618
2006	0.5037654	0.4273223	0.0764431	0.0451884
2007	0.4927018	0.4090434	0.0836584	0.0477691
2008	0.735085	0.616735	0.1183501	0.0505976
2009	-0.0358437	0.5145633	-0.550407	0.1532927
2010	-0.0025786	0.6011008	-0.6036794	0.1511667
2011	-0.0039407	0.6208644	-0.624805	0.1504821
2012	-0.0447267	0.6071622	-0.6518889	0.1499465
2013	0.1157106	0.7670555	-0.6513449	0.1496468
2014	-0.0828383	0.5813539	-0.6641922	0.1493657
2015	-0.1287435	0.5400284	-0.6687719	0.1490617
2016	-0.1456426	0.5235052	-0.6691478	0.1484245

Test: Ho: difference in coefficients not systematic
chi2(45) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 3803.18
Prob>chi2 = 0.0000

Hausman Specification Test Results - Model 2A

	FE	RE	Difference	S.E.
LABOUR_MARKET_TRANSITIONS				
Remains Unemployed	1.264935	1.523899	-0.2589641	0.047585
Remains Long-term Sick	1.504873	2.550461	-1.045589	0.0630441
Remains Economically Inactive	-0.0961153	0.2227738	-0.3188891	0.0288728
Unemployed to Employed/Self Employed	-0.6262232	-0.4779681	-0.1482551	0.0259242
Unemployed to Long Term Sick	2.333644	3.221628	-0.8879845	0.0663723
Unemployed to Economically Inactive	0.0041271	0.3810581	-0.376931	0.0410438
Employed/Self Employed to Unemployed	2.066499	2.232079	-0.1655803	0.0268542
Employed/Self Employed to Long Term Sick	3.518324	4.066764	-0.5484406	0.0458511
Employed/Self Employed to Economically Inactive	-0.2886429	-0.0955401	-0.1931028	0.0194399
Long Term Sick to Employed/Self Employed	-1.428659	-0.7909227	-0.6377362	0.0602286
Long Term Sick to Unemployed	1.365429	2.407825	-1.042395	0.0747117
Long Term Sick to Economically Inactive	0.2253349	1.157544	-0.9322088	0.0549549
Economically Inactive to Employed/Self Employed	-0.4994655	-0.2794758	-0.2199897	0.0185976
Economically Inactive to Unemployed	0.7510118	1.085597	-0.3345853	0.0423168
Economically Inactive to Long Term Sick	1.335547	2.253084	-0.9175376	0.0575737
GENERALHEALTH				
Good	0.7630615	1.095876	-0.3328144	0.0120639
Fair	2.229017	3.037819	-0.8088028	0.0173396
Poor	4.831012	6.08102	-1.250008	0.0255693
MARSTAT				
Married or Civil Partnership	0.032676	-0.1444917	0.1771678	0.0450321
Separated or Divorced	0.2039456	0.4567057	-0.2527602	0.0566825
Widowed or Surviving Partner	1.503063	0.9805785	0.5224843	0.1149157
EDUCATION				
Other Higher Degree	-0.0137084	0.0271483	-0.0408567	0.1151876
A Level	-0.2185872	-0.0763456	-0.1422416	0.0766391
GCSE	-0.129817	-0.0450232	-0.0847938	0.0971328
Other Qualification	0.0706194	-0.0484309	0.1190502	0.1483263
No Qualification	-0.049875	0.0443241	-0.0941991	0.1556016
LOG_HH_INCOME_PERCAPITA	-0.124485	-0.175115	0.0506299	0.008442
NUMBER_KIDS	-0.0065237	-0.005055	-0.0014687	0.0129378
ALL_AGE_BANDS				
Aged: 26-35	0.3205641	0.4761766	-0.1556125	0.0398112
Aged: 36-45	0.4507596	0.597928	-0.1471684	0.0644109
Aged: 46-55	0.3687724	0.4507335	-0.0819612	0.0872353
Aged: 56-65	-0.0715169	-0.3103697	0.2388528	0.1106244
Year				
1993	-0.0388234	-0.0517476	0.0129242	0.012098
1994	0.0100555	-0.0066158	0.0166712	0.0146003
1995	0.1444642	0.130218	0.0142462	0.0166324
1996	0.1702476	0.1475361	0.0227115	0.0188301
1997	0.14354	0.1363419	0.0071981	0.0211849
1998	0.0450665	0.0325473	0.0125192	0.0249053
1999	0.1191149	0.1598164	-0.0407015	0.0269461
2000	0.1676794	0.1476688	0.0200105	0.0307231
2001	0.1698724	0.1685068	0.0013656	0.0332645
2002	0.0293026	0.0475384	-0.0182358	0.0361476
2003	-0.0659189	-0.0422022	-0.0237167	0.0385905
2004	0.0844783	0.1103908	-0.0259125	0.0412277
2005	0.2180449	0.2503939	-0.032349	0.0439331
2006	0.2294738	0.2760924	-0.0466186	0.0468668
2007	0.2002953	0.2434678	-0.0431725	0.0498503
2008	0.4270242	0.4689127	-0.0418885	0.0530788
2010	0.2604735	0.4769904	-0.2165169	0.1762361
2011	0.235043	0.5024167	-0.2673737	0.1740254
2012	0.1690302	0.4610824	-0.2920522	0.1732782
2013	0.3469548	0.6533947	-0.3064399	0.172887
2014	0.1438701	0.4662262	-0.3223562	0.1726388
2015	0.0726585	0.4036418	-0.3309833	0.1724066
2016	0.0558496	0.3893515	-0.3335019	0.1723335

Test: Ho: difference in coefficients not systematic
chi2(55) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 3442.61
Prob>chi2 = 0.0000

Hausman Specification Test Results - Model 2B

	FE	RE	Difference	S.E.
LABOUR_MARKET_STATUS				
Unemployed	0.7510118	1.085597	-0.3345853	0.0423168
Long-term Sickness	1.335547	2.253084	-0.9175376	0.0575737
Economically Inactive	0.2253349	1.157544	-0.9322088	0.0549549
LABOUR_MARKET_TRANSITIONS				
Remains Unemployed	0.5139233	0.438302	0.0756213	0.049299
Remains Long-term Sick	0.1693263	0.2973773	-0.128051	0.0491679
Remains Economically Inactive	-0.3214502	-0.93477	0.6133197	0.0515642
Unemployed to Employed/Self Employed	-0.6262232	-0.4779681	-0.1482551	0.0259242
Unemployed to Long Term Sick	0.9980974	0.9685442	0.0295531	0.0677748
Unemployed to Economically Inactive	-0.2212078	-0.7764856	0.5552778	0.0599756
Employed/Self Employed to Unemployed	1.315487	1.146482	0.1690051	0.0444974
Employed/Self Employed to Long Term Sick	2.182777	1.81368	0.369097	0.0600566
Employed/Self Employed to Economically Inactive	-0.5139778	-1.253084	0.739106	0.0540884
Long Term Sick to Employed/Self Employed	-1.428659	-0.7909227	-0.6377362	0.0602286
Long Term Sick to Unemployed	0.6144173	1.322227	-0.7078101	0.0780864
Economically Inactive to Employed/Self Employed	-0.4994655	-0.2794758	-0.2199897	0.0185976
GENERALHEALTH				
Good	0.7630615	1.095876	-0.3328144	0.0120639
Fair	2.229017	3.037819	-0.8088028	0.0173396
Poor	4.831012	6.08102	-1.250008	0.0255693
MARSTAT				
Married or Civil Partnership	0.032676	-0.1444917	0.1771678	0.0450321
Separated or Divorced	0.2039456	0.4567057	-0.2527602	0.0566825
Widowed or Surviving Partner	1.503063	0.9805785	0.5224843	0.1149157
EDUCATION				
Other Higher Degree	-0.0137084	0.0271483	-0.0408567	0.1151876
A Level	-0.2185872	-0.0763456	-0.1422416	0.0766391
GCSE	-0.129817	-0.0450232	-0.0847938	0.0971328
Other Qualification	0.0706194	-0.0484309	0.1190502	0.1483263
No Qualification	-0.049875	0.0443241	-0.0941991	0.1556016
LOG_HH_INCOME_PERCAPITA	-0.124485	-0.175115	0.0506299	0.008442
NUMBER_KIDS	-0.0065237	-0.005055	-0.0014687	0.0129378
ALL_AGE_BANDS				
Aged: 26-35	0.3205641	0.4761766	-0.1556125	0.0398112
Aged: 36-45	0.4507596	0.597928	-0.1471684	0.0644109
Aged: 46-55	0.3687724	0.4507335	-0.0819612	0.0872353
Aged: 56-65	-0.0715169	-0.3103697	0.2388528	0.1106244
Year				
1993	-0.0388234	-0.0517476	0.0129242	0.012098
1994	0.0100555	-0.0066158	0.0166712	0.0146003
1995	0.1444642	0.130218	0.0142462	0.0166324
1996	0.1702476	0.1475361	0.0227115	0.0188301
1997	0.14354	0.1363419	0.0071981	0.0211849
1998	0.0450665	0.0325473	0.0125192	0.0249053
1999	0.1191149	0.1598164	-0.0407015	0.0269461
2000	0.1676794	0.1476688	0.0200105	0.0307231
2001	0.1698724	0.1685068	0.0013656	0.0332645
2002	0.0293026	0.0475384	-0.0182358	0.0361476
2003	-0.0659189	-0.0422022	-0.0237167	0.0385905
2004	0.0844783	0.1103908	-0.0259125	0.0412277
2005	0.2180449	0.2503939	-0.032349	0.0439331
2006	0.2294738	0.2760924	-0.0466186	0.0468668
2007	0.2002953	0.2434678	-0.0431725	0.0498503
2008	0.4270242	0.4689127	-0.0418885	0.0530788
2010	0.2604735	0.4769904	-0.2165169	0.1762361
2011	0.235043	0.5024167	-0.2673737	0.1740254
2012	0.1690302	0.4610824	-0.2920522	0.1732782
2013	0.3469548	0.6533947	-0.3064399	0.172887
2014	0.1438701	0.4662262	-0.3223562	0.1726388
2015	0.0726585	0.4036418	-0.3309833	0.1724066
2016	0.0558496	0.3893515	-0.3335019	0.1723335

Test: Ho: difference in coefficients not systematic
chi2(55) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 3442.61
Prob>chi2 = 0.0000

A.1.5 Results of Levene's Test for Equality of Variances

Levene's Test for Equality of Variances - Check for Heteroscedasticity

Transition: Unemployed to Employed / Self_Employed	**Mean**	**Std Dev**	**Freq**
0	23.240751	5.591956	298,159
1	22.43762	5.517474	5,226
Total	23.226916	5.591649	303,385

W0 = 0.0802787	df(1, 303383)	Pr>F =	0.77692027
W50 = 0.14685311	df(1, 303383)	Pr>F =	0.70156124
W10 = 0.00553531	df(1, 303383)	Pr>F =	0.94069242

Transition: Economically Inactive to Employed / Self_Employed	**Mean**	**Std Dev**	**Freq**
0	23.254346	5.597365	292,731
1	22.473249	5.3780383	10,654
Total	23.226916	5.591649	303,385

W0 = 6.8558009	df(1, 303383)	Pr>F =	0.00883583
W50 = 2.247394	df(1, 303383)	Pr>F =	0.13384067
W10 = 4.5375921	df(1, 303383)	Pr>F =	0.03315901

Note: Only in the case of the above 2 variables was the Null Hypothesis of Homoscedasticity accepted.

A.1.6 Results of Robustness Checks - Random Effects and OLS

Robustness Check for Model 1A

VARIABLES	(1) FE-Model 1A	(2) OLS-Model 1A
Self Employed	-0.0380	-0.209***
	(0.0501)	(0.0279)
Unemployed	1.676***	1.644***
	(0.0567)	(0.0467)
Retired	-0.273***	-0.231***
	(0.0613)	(0.0393)
Maternity Leave	-0.0425	0.324***
	(0.0990)	(0.100)
Family Care	0.629***	1.043***
	(0.0560)	(0.0360)
Full Time Student	-0.0120	0.238***
	(0.0582)	(0.0388)
Long Term Sickness	2.081***	2.542***
	(0.0978)	(0.0644)
Government Training Scheme	-0.0821	-0.388*
	(0.212)	(0.201)
Unpaid Worker in Family Business	0.155	1.110**
	(0.527)	(0.437)
Apprenticeship	-0.112	-0.971***
	(0.336)	(0.307)
General Health Level = 2, Good	0.748***	1.494***
	(0.0228)	(0.0181)
General Health Level = 3, Fair	2.192***	3.977***
	(0.0379)	(0.0299)
General Health Level = 4, Poor	4.808***	7.526***
	(0.0703)	(0.0560)
Marital Status = 2, Married or Civil Partnership	0.0431	-0.181***
	(0.0566)	(0.0247)
Marital Status = 3, Separated or Divorced	0.267***	0.606***
	(0.0839)	(0.0358)
Marital Status = 4, Widowed or Surviving Partner	1.540***	0.987***
	(0.184)	(0.0746)
Highest Education Levels = 2, Other Higher Degree	0.0142	-0.0486
	(0.123)	(0.0308)
Highest Education Levels = 3, A Level	-0.0750	-0.125***
	(0.0892)	(0.0254)
Highest Education Levels = 4, GCSE	-0.0724	-0.186***
	(0.103)	(0.0251)
Highest Education Levels = 5, Other Qualification	-0.0330	-0.322***
	(0.151)	(0.0340)
Highest Education Levels = 9, No Qualification	-0.209	-0.299***
	(0.143)	(0.0337)
Log Household Income Per Capita	-0.126***	-0.226***
	(0.0173)	(0.0131)
Number of Children	-0.0432**	-0.0612***
	(0.0199)	(0.0102)
Age Bands = 2, Aged: 26-35	0.292***	0.583***
	(0.0564)	(0.0330)
Age Bands = 3, Aged: 36-45	0.399***	0.813***
	(0.0793)	(0.0357)
Age Bands = 4, Aged: 46-55	0.250**	0.715***
	(0.0980)	(0.0373)
Age Bands = 5, Aged: 56-65	-0.238**	-0.114***
	(0.117)	(0.0414)
Constant	22.48***	21.91***
	(0.182)	(0.109)
Observations	387,242	387,242
R-squared	0.050	0.167
Number of pidp	86,651	
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Check for Model 1B

VARIABLES	(1) FE-Model 1B	(2) OLS-Model 1B
Labour Market Status = 2, Unemployed	1.645***	1.671***
	(0.0562)	(0.0464)
Labour Market Status = 3, Long-term Sickness	2.104***	2.598***
	(0.0964)	(0.0641)
Labour Market Status = 4, Economically Inactive	0.144***	0.445***
	(0.0356)	(0.0228)
General Health Level = 2, Good	0.750***	1.506***
	(0.0228)	(0.0181)
General Health Level = 3, Fair	2.195***	4.003***
	(0.0379)	(0.0300)
General Health Level = 4, Poor	4.807***	7.537***
	(0.0702)	(0.0560)
Marital Status = 2, Married or Civil Partnership	0.0694	-0.158***
	(0.0566)	(0.0246)
Marital Status = 3, Separated or Divorced	0.286***	0.634***
	(0.0839)	(0.0358)
Marital Status = 4, Widowed or Surviving Partner	1.497***	0.954***
	(0.184)	(0.0745)
Highest Education Levels = 2, Other Higher Degree	-0.0529	-0.0470
	(0.122)	(0.0308)
Highest Education Levels = 3, A Level	-0.178**	-0.123***
	(0.0863)	(0.0254)
Highest Education Levels = 4, GCSE	-0.215**	-0.164***
	(0.0987)	(0.0251)
Highest Education Levels = 5, Other Qualification	-0.171	-0.280***
	(0.148)	(0.0340)
Highest Education Levels = 9, No Qualification	-0.370***	-0.245***
	(0.139)	(0.0337)
Log Household Income Per Capita	-0.122***	-0.223***
	(0.0173)	(0.0130)
Number of Children	-0.0320	-0.0259**
	(0.0199)	(0.0102)
Age Bands = 2, Aged: 26-35	0.325***	0.670***
	(0.0564)	(0.0308)
Age Bands = 3, Aged: 36-45	0.443***	0.868***
	(0.0792)	(0.0337)
Age Bands = 4, Aged: 46-55	0.315***	0.766***
	(0.0978)	(0.0354)
Age Bands = 5, Aged: 56-65	-0.206*	-0.263***
	(0.117)	(0.0367)
Constant	22.51***	21.79***
	(0.180)	(0.108)
Observations	387,242	387,242
R-squared	0.050	0.165
Number of pidp	86,651	
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Check for Model 2A

VARIABLES	(1) FE-Model 2A	(2) OLS-Model 2A
Labour Market Transitions = 2, Remains Unemployed	1.265***	1.287***
	(0.110)	(0.0814)
Labour Market Transitions = 3, Remains Long-term Sick	1.505***	2.173***
	(0.150)	(0.0798)
Labour Market Transitions = 4, Remains Economically Inactive	-0.0961*	0.437***
	(0.0529)	(0.0289)
Labour Market Transitions = 5, Unemployed to Employed/Self Employed	-0.626***	-0.454***
	(0.0773)	(0.0753)
Labour Market Transitions = 6, Unemployed to Long Term Sick	2.334***	3.221***
	(0.222)	(0.220)
Labour Market Transitions = 7, Unemployed to Economically Inactive	0.00413	0.585***
	(0.113)	(0.112)
Labour Market Transitions = 8, Employed/Self Employed to Unemployed	2.066***	2.317***
	(0.101)	(0.102)
Labour Market Transitions = 9, Employed/Self Employed to Long Term Sick	3.518***	4.091***
	(0.226)	(0.240)
Labour Market Transitions = 10, Employed/Self Employed to Economically Inactive	-0.289***	0.150**
	(0.0593)	(0.0582)
Labour Market Transitions = 11, Long Term Sick to Employed/Self Employed	-1.429***	-0.556**
	(0.270)	(0.256)
Labour Market Transitions = 12, Long Term Sick to Unemployed	1.365***	2.595***
	(0.226)	(0.234)
Labour Market Transitions = 13, Long Term Sick to Economically Inactive	0.225	1.327***
	(0.163)	(0.156)
Labour Market Transitions = 14, Economically Inactive to Employed/Self Employed	-0.499***	-0.0451
	(0.0526)	(0.0525)
Labour Market Transitions = 15, Economically Inactive to Unemployed	0.751***	1.241***
	(0.114)	(0.111)
Labour Market Transitions = 16, Economically Inactive to Long Term Sick	1.336***	2.366***
	(0.189)	(0.188)
General Health Level = 2, Good	0.763***	1.517***
	(0.0260)	(0.0206)
General Health Level = 3, Fair	2.229***	4.026***
	(0.0427)	(0.0337)
General Health Level = 4, Poor	4.831***	7.579***
	(0.0789)	(0.0632)
Marital Status = 2, Married or Civil Partnership	0.0327	-0.151***
	(0.0658)	(0.0279)
Marital Status = 3, Separated or Divorced	0.204**	0.616***
	(0.0959)	(0.0402)
Marital Status = 4, Widowed or Surviving Partner	1.503***	0.853***
	(0.208)	(0.0825)
Highest Education Levels = 2, Other Higher Degree	-0.0137	-0.0546
	(0.151)	(0.0348)
Highest Education Levels = 3, A Level	-0.219**	-0.165***
	(0.102)	(0.0287)
Highest Education Levels = 4, GCSE	-0.130	-0.159***
	(0.122)	(0.0286)
Highest Education Levels = 5, Other Qualification	0.0706	-0.262***
	(0.193)	(0.0382)
Highest Education Levels = 9, No Qualification	-0.0499	-0.214***
	(0.198)	(0.0388)
Log Household Income Per Capita	-0.124***	-0.223***
	(0.0206)	(0.0155)
Number of Children	-0.00652	-0.00629
	(0.0234)	(0.0118)
Age Bands = 2, Aged: 26-35	0.321***	0.579***
	(0.0661)	(0.0368)
Age Bands = 3, Aged: 36-45	0.451***	0.754***
	(0.0915)	(0.0398)
Age Bands = 4, Aged: 46-55	0.369***	0.656***
	(0.112)	(0.0413)
Age Bands = 5, Aged: 56-65	-0.0715	-0.359***
	(0.133)	(0.0427)
Constant	22.52***	22.03***
	(0.208)	(0.128)
Observations	300,357	300,357
R-squared	0.053	0.169
Number of pidp	67,201	
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Check for Model 2B

VARIABLES	(1) FE-Model 2B	(2) OLS-Model 2B
Labour Market Status = 2, Unemployed	0.751***	1.241***
	(0.114)	(0.111)
Labour Market Status = 3, Long-term Sickness	1.336***	2.366***
	(0.189)	(0.188)
Labour Market Status = 4, Economically Inactive	0.225	1.327***
	(0.163)	(0.156)
Labour Market Transitions = 2, Remains Unemployed	0.514***	0.0463
	(0.140)	(0.135)
Labour Market Transitions = 3, Remains Long-term Sick	0.169	-0.192
	(0.183)	(0.198)
Labour Market Transitions = 4, Remains Economically Inactive	-0.321**	-0.890***
	(0.158)	(0.157)
Labour Market Transitions = 5, Unemployed to Employed/Self Employed	-0.626***	-0.454***
	(0.0773)	(0.0753)
Labour Market Transitions = 6, Unemployed to Long Term Sick	0.998***	0.855***
	(0.263)	(0.286)
Labour Market Transitions = 7, Unemployed to Economically Inactive	-0.221	-0.742***
	(0.187)	(0.191)
Labour Market Transitions = 8, Employed/Self Employed to Unemployed	1.315***	1.076***
	(0.144)	(0.149)
Labour Market Transitions = 9, Employed/Self Employed to Long Term Sick	2.183***	1.726***
	(0.277)	(0.301)
Labour Market Transitions = 10, Employed/Self Employed to Economically Inactive	-0.514***	-1.177***
	(0.167)	(0.165)
Labour Market Transitions = 11, Long Term Sick to Employed/Self Employed	-1.429***	-0.556**
	(0.270)	(0.256)
Labour Market Transitions = 12, Long Term Sick to Unemployed	0.614**	1.354***
	(0.243)	(0.258)
Labour Market Transitions = 14, Economically Inactive to Employed/Self Employed	-0.499***	-0.0451
	(0.0526)	(0.0525)
General Health Level = 2, Good	0.763***	1.517***
	(0.0260)	(0.0206)
General Health Level = 3, Fair	2.229***	4.026***
	(0.0427)	(0.0337)
General Health Level = 4, Poor	4.831***	7.579***
	(0.0789)	(0.0632)
Marital Status = 2, Married or Civil Partnership	0.0327	-0.151***
	(0.0658)	(0.0279)
Marital Status = 3, Separated or Divorced	0.204**	0.616***
	(0.0959)	(0.0402)
Marital Status = 4, Widowed or Surviving Partner	1.503***	0.853***
	(0.208)	(0.0825)
Highest Education Levels = 2, Other Higher Degree	-0.0137	-0.0546
	(0.151)	(0.0348)
Highest Education Levels = 3, A Level	-0.219**	-0.165***
	(0.102)	(0.0287)
Highest Education Levels = 4, GCSE	-0.130	-0.159***
	(0.122)	(0.0286)
Highest Education Levels = 5, Other Qualification	0.0706	-0.262***
	(0.193)	(0.0382)
Highest Education Levels = 9, No Qualification	-0.0499	-0.214***
	(0.198)	(0.0388)
Log Household Income Per Capita	-0.124***	-0.223***
	(0.0206)	(0.0155)
Number of Children	-0.00652	-0.00629
	(0.0234)	(0.0118)
Age Bands = 2, Aged: 26-35	0.321***	0.579***
	(0.0661)	(0.0368)
Age Bands = 3, Aged: 36-45	0.451***	0.754***
	(0.0915)	(0.0398)
Age Bands = 4, Aged: 46-55	0.369***	0.656***
	(0.112)	(0.0413)
Age Bands = 5, Aged: 56-65	-0.0715	-0.359***
	(0.133)	(0.0427)
Constant	22.52***	22.03***
	(0.208)	(0.128)
Observations	300,357	300,357
R-squared	0.053	0.169
Number of pidp	67,201	
Year Dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.2 Appendix to Chapter-3

A.2.1 Summary Statistics for Weekly Pay – Minimal Support Group

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay1	11107	115.1522	153.9384	0	3258.858
weeklypay2	11107	116.4615	175.7996	0	8759.914
weeklypay3	11107	115.7861	154.2485	0	3277.618
weeklypay4	11107	115.9515	163.8313	0	6272.883
weeklypay5	11107	116.7633	181.9329	0	8105.939
weeklypay6	11107	116.0317	159.4618	0	5018.276
weeklypay7	11107	114.7719	152.3922	0	4456.227
weeklypay8	11107	115.0805	154.303	0	4456.227
weeklypay9	11107	115.1622	150.9402	0	3229.986
weeklypay10	11107	116.0266	149.9716	0	2374.065
weeklypay11	11107	116.1811	151.4081	0	2555.428
weeklypay12	11107	115.3948	147.5237	0	1798.534
weeklypay13	11107	114.4388	145.7659	0	1723.448
weeklypay14	11107	114.4831	145.2017	0	1723.448
weeklypay15	11107	115.1574	154.3035	0	3795.931
weeklypay16	11107	113.9901	146.9096	0	2030.233
weeklypay17	11107	113.3229	142.046	0	1796.584
weeklypay18	11107	113.6388	143.1921	0	3311.786
weeklypay19	11107	113.5289	144.0979	0	2375.428
weeklypay20	11107	112.6271	145.4327	0	4220.78
weeklypay21	11107	113.3239	150.6482	0	3463.325
weeklypay22	11107	114.272	165.9708	0	8344.043
weeklypay23	11107	113.2252	153.0881	0	5317.59
weeklypay24	11107	112.3811	154.1169	0	5317.59
weeklypay25	11107	112.531	161.0119	0	5674.55
weeklypay26	11107	111.8108	150.2002	0	3637.379
weeklypay27	11107	111.3737	147.9221	0	3781.608
weeklypay28	11107	110.6207	141.4271	0	2955.507
weeklypay29	11107	110.8776	140.6529	0	2653.883
weeklypay30	11107	110.6084	142.8063	0	2653.883
weeklypay31	11107	110.0207	142.312	0	3606.039
weeklypay32	11107	108.9531	141.1354	0	4786.094

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay33	11107	109.0803	137.7516	0	2936.779
weeklypay34	11107	109.4716	158.9115	0	7849.14
weeklypay35	11107	109.1222	142.1318	0	3420.561
weeklypay36	11107	109.4747	150.1134	0	4712.857
weeklypay37	11107	109.0791	155.5592	0	5290.464
weeklypay38	11107	108.1445	140.4189	0	4767.201
weeklypay39	11107	108.145	136.9059	0	4780.122
weeklypay40	11107	109.0901	140.8554	0	4086.577
weeklypay41	11107	109.15	134.388	0	4057.117
weeklypay42	11107	109.849	137.7862	0	4753.449
weeklypay43	11107	110.1343	123.2826	0	2887.416
weeklypay44	11107	111.6039	118.6192	0	1857.275
weeklypay45	11107	112.7005	108.7958	0	1384.397
weeklypay46	11107	116.4765	107.4119	0	1934.235
weeklypay47	11107	122.0689	137.9491	0	7461.475
weeklypay48	11107	126.1846	131.6008	0	7461.475
weeklypay49	11107	131.7922	126.9728	0	7461.475
weeklypay50	11107	137.5752	125.6743	0	7461.475
weeklypay51	11107	143.3981	105.0196	0	2411.569
weeklypay52	11107	148.0936	96.54212	0	1954.6
weeklypay53	11107	162.7479	92.28462	0.0519355	1248.656
weeklypay54	11107	160.4752	97.97189	0	2594.02
weeklypay55	11107	160.9282	100.4397	0	2587.726
weeklypay56	11107	161.5179	104.8245	0	1989.729
weeklypay57	11107	161.5845	109.4779	0	1892.864
weeklypay58	11107	161.702	114.8248	0	3712.15
weeklypay59	11107	160.466	108.3472	0	1905.271
weeklypay60	11107	159.7946	112.2525	0	1919.97
weeklypay61	11107	160.1884	118.2252	0	2904.991
weeklypay62	11107	160.7895	122.6408	0	3843.839
weeklypay63	11107	161.3008	120.9246	0	2409.764
weeklypay64	11107	161.7135	125.2431	0	3111.51
weeklypay65	11107	161.7539	138.1546	0	7382.236
weeklypay66	11107	161.6951	124.0793	0	1803.211
weeklypay67	11107	161.4298	125.7844	0	2745.215

Week No	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
weeklypay68	11107	162.2309	127.9491	0	2030.295
weeklypay69	11107	162.1052	126.759	0	2417.219
weeklypay70	11107	164.4685	150.7959	0	5664.898
weeklypay71	11107	165.0045	144.7656	0	4370
weeklypay72	11107	165.038	145.9348	0	4370
weeklypay73	11107	166.1208	158.1365	0	5308.786
weeklypay74	11107	166.6542	157.5165	0	5569.89
weeklypay75	11107	165.9614	164.4992	0	8464.085
weeklypay76	11107	166.1502	155.7747	0	6357.294
weeklypay77	11107	167.4445	157.5085	0	4960.007
weeklypay78	11107	168.3607	166.1436	0	5709.601
weeklypay79	11107	167.8289	154.7421	0	4528.946
weeklypay80	11107	170.0684	177.1962	0	6885.654
weeklypay81	11107	171.3923	173.1932	0	5179.237
weeklypay82	11107	170.4592	172.3256	0	5589.651
weeklypay83	11107	170.617	181.4411	0	8097.577
weeklypay84	11107	169.6527	173.5325	0	5734.038
weeklypay85	11107	169.7658	179.9171	0	7204.986
weeklypay86	11107	170.3936	173.8117	0	5724.781
weeklypay87	11107	170.8036	182.6546	0	5724.781
weeklypay88	11107	170.4225	171.4912	0	4837.973
weeklypay89	11107	169.9243	162.9453	0	5452.912
weeklypay90	11107	168.59	151.3515	0	3580.928
weeklypay91	11107	169.8885	171.6832	0	6186.253
weeklypay92	11107	172.3701	206.2345	0	8248.337
weeklypay93	11107	171.1048	187.3924	0	6646.628
weeklypay94	11107	169.5925	166.9641	0	5401.919
weeklypay95	11107	169.4146	162.1699	0	5065.886
weeklypay96	11107	171.634	188.2871	0	7030.526
weeklypay97	11107	170.3939	177.1809	0	6019.95
weeklypay98	11107	169.7053	167.2129	0	5240.925
weeklypay99	11107	169.6073	172.3433	0	6107.143
weeklypay100	11107	169.3782	154.7537	0	2982.326
weeklypay101	11107	171.9504	190.1458	0	8274.892
weeklypay102	11107	172.1624	179.404	0	5089.298

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay103	11107	171.4195	172.833	0	6236.648
weeklypay104	11107	170.7739	157.9687	0	3178.208
weeklypay105	11107	172.3334	179.4076	0	8324.586
weeklypay106	11107	172.3275	171.2534	0	6065.594
weeklypay107	11107	171.7073	161.9748	0	3077.078
weeklypay108	11107	171.9636	159.0939	0	4164.813
weeklypay109	11107	173.1403	177.516	0	7018.597
weeklypay110	11107	174.8782	186.7087	0	6671.3
weeklypay111	11107	174.225	169.9104	0	6263.142
weeklypay112	11107	173.7665	164.7244	0	5736.043
weeklypay113	11107	174.5577	161.722	0	3483.584
weeklypay114	11107	174.338	156.1964	0	2698.471
weeklypay115	11107	176.0743	178.7697	0	8090.227
weeklypay116	11107	176.1185	170.7843	0	5332.754
weeklypay117	11107	175.8769	163.3366	0	3413.077
weeklypay118	11107	175.0652	160.8588	0	2996.403
weeklypay119	11107	175.178	159.8102	0	3115.256
weeklypay120	11107	175.75	165.3091	0	4444.404
weeklypay121	11107	176.0522	166.2216	0	4585.034
weeklypay122	11107	176.3677	173.3215	0	5309.006
weeklypay123	11107	176.7158	169.1294	0	4578.174
weeklypay124	11107	178.8428	198.1663	0	8581.817
weeklypay125	11107	177.2121	166.1943	0	3818.021
weeklypay126	11107	178.5481	176.8038	0	5020.744
weeklypay127	11107	177.343	165.8217	0	3818.021
weeklypay128	11107	176.9012	157.2914	0	2103.505
weeklypay129	11107	177.6031	167.388	0	4674.227
weeklypay130	11107	176.2235	153.6449	0	993.4371

A.2.2 Summary Statistics for Weekly Pay – Moderate Support Group

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay1	10377	113.7715	165.3884	0	7590.536
weeklypay2	10377	113.5803	150.4772	0	3036.214
weeklypay3	10377	113.2714	146.7765	0	2094.093
weeklypay4	10377	112.6219	145.9211	0	2436.936
weeklypay5	10377	113.3687	147.0965	0	2436.936
weeklypay6	10377	114.2225	151.1642	0	3577.057
weeklypay7	10377	115.5488	165.8907	0	7153.537
weeklypay8	10377	115.2333	158.5953	0	5323.367
weeklypay9	10377	115.2195	156.1523	0	4508.606
weeklypay10	10377	114.9547	148.1874	0	2799.463
weeklypay11	10377	116.035	166.7092	0	5903.943
weeklypay12	10377	115.8302	157.0051	0	4427.957
weeklypay13	10377	114.4335	147.8002	0	2443.686
weeklypay14	10377	114.9645	160.073	0	4765.75
weeklypay15	10377	116.0096	178.6624	0	7574.533
weeklypay16	10377	113.8958	152.2541	0	4765.75
weeklypay17	10377	112.9695	147.7916	0	4113.643
weeklypay18	10377	113.4899	153.8614	0	5663.821
weeklypay19	10377	114.1529	151.6291	0	4176.449
weeklypay20	10377	114.5588	152.8344	0	4170.525
weeklypay21	10377	113.6617	151.5701	0	4170.525
weeklypay22	10377	113.7637	148.4542	0	3396.662
weeklypay23	10377	113.6271	151.3514	0	3396.662
weeklypay24	10377	112.7966	146.8058	0	3396.662
weeklypay25	10377	113.4196	154.6231	0	4868.89
weeklypay26	10377	112.8805	143.1103	0	1952.229
weeklypay27	10377	111.702	142.5739	0	3848.047
weeklypay28	10377	111.1025	136.8107	0	1695.025
weeklypay29	10377	112.1657	140.0039	0	2281.88
weeklypay30	10377	112.4693	139.7206	0	1805.333
weeklypay31	10377	111.253	138.3839	0	1800.9
weeklypay32	10377	110.2615	138.471	0	2964.768
weeklypay33	10377	110.3053	139.6256	0	3738.716

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay34	10377	109.3158	135.543	0	3738.716
weeklypay35	10377	110.043	140.9191	0	4058.94
weeklypay36	10377	109.723	137.601	0	4058.94
weeklypay37	10377	108.907	134.0215	0	4058.94
weeklypay38	10377	107.811	128.9668	0	3479.091
weeklypay39	10377	108.427	128.4209	0	3097.682
weeklypay40	10377	109.2955	131.6327	0	4185
weeklypay41	10377	109.8297	124.1691	0	1748.4
weeklypay42	10377	110.6552	122.0018	0	2334.698
weeklypay43	10377	111.0048	121.4129	0	3112.931
weeklypay44	10377	112.2395	116.2218	0	2577.75
weeklypay45	10377	114.3563	113.3923	0	2577.75
weeklypay46	10377	117.93	114.0405	0	3550
weeklypay47	10377	121.9292	108.8234	0	3550
weeklypay48	10377	127.7251	126.7358	0	6568.506
weeklypay49	10377	133.2168	111.0235	0	3550
weeklypay50	10377	139.2963	107.9261	0	3343.217
weeklypay51	10377	144.6081	104.7485	0	3310.302
weeklypay52	10377	150.1741	95.24397	0	1450.39
weeklypay53	10377	164.786	93.30223	0.525	1236.893
weeklypay54	10377	162.234	99.38019	0	2540.861
weeklypay55	10377	162.1882	99.90838	0	2579.6
weeklypay56	10377	162.2303	108.3539	0	2888.779
weeklypay57	10377	160.6196	105.8224	0	2297.951
weeklypay58	10377	161.6369	109.4744	0	2300.804
weeklypay59	10377	161.9443	111.0272	0	1714.286
weeklypay60	10377	161.6859	113.4878	0	1427.884
weeklypay61	10377	162.9573	121.9535	0	3823.914
weeklypay62	10377	163.0387	121.1154	0	2915.259
weeklypay63	10377	163.5219	123.8246	0	3493.914
weeklypay64	10377	165.5392	149.7683	0	8606.203
weeklypay65	10377	164.2731	127.5593	0	3341.99
weeklypay66	10377	164.2337	129.2102	0	3900.592
weeklypay67	10377	164.8808	142.307	0	5087.058
weeklypay68	10377	165.0875	136.2043	0	3313.041

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay69	10377	163.6289	127.7272	0	2564.286
weeklypay70	10377	164.4582	127.4392	0	1600.493
weeklypay71	10377	165.2969	128.4776	0	1490.65
weeklypay72	10377	166.6538	131.3088	0	1722.671
weeklypay73	10377	166.7934	130.1141	0	1589.51
weeklypay74	10377	167.614	137.3799	0	3077.521
weeklypay75	10377	168.4016	155.2149	0	7773.529
weeklypay76	10377	169.5842	146.3608	0	4016.726
weeklypay77	10377	171.2756	153.8739	0	3425.92
weeklypay78	10377	172.0621	169.3792	0	5663.824
weeklypay79	10377	172.6786	157.0199	0	3336.286
weeklypay80	10377	173.5608	169.3364	0	4857.122
weeklypay81	10377	172.015	157.91	0	5635.271
weeklypay82	10377	172.963	164.144	0	6059.766
weeklypay83	10377	175.2969	186.1893	0	5173.424
weeklypay84	10377	175.5776	170.5216	0	5722.516
weeklypay85	10377	176.2115	172.865	0	4832.318
weeklypay86	10377	175.593	178.0549	0	5678.651
weeklypay87	10377	176.0781	179.958	0	6108.271
weeklypay88	10377	175.6555	174.9471	0	6070.984
weeklypay89	10377	175.1016	168.9877	0	6056.07
weeklypay90	10377	174.1944	163.3656	0	4325.765
weeklypay91	10377	174.1743	163.6454	0	5844.808
weeklypay92	10377	175.517	167.1461	0	5844.808
weeklypay93	10377	176.2687	177.6701	0	5844.808
weeklypay94	10377	177.2024	199.0277	0	5905.85
weeklypay95	10377	176.319	189.2443	0	5454.241
weeklypay96	10377	176.3688	180.5721	0	5391.912
weeklypay97	10377	177.1636	191.2659	0	8646.319
weeklypay98	10377	175.5615	161.7656	0	5028.199
weeklypay99	10377	176.1996	169.1535	0	5174.964
weeklypay100	10377	178.0305	186.2796	0	6620.823
weeklypay101	10377	179.2112	208.6639	0	7315.318
weeklypay102	10377	176.5331	175.8624	0	6155.016
weeklypay103	10377	176.0107	155.328	0	2569.487

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay104	10377	177.6675	161.0153	0	2816.591
weeklypay105	10377	180.3462	179.5366	0	4766.693
weeklypay106	10377	180.0515	184.8468	0	6158.867
weeklypay107	10377	179.1353	166.9969	0	4141.08
weeklypay108	10377	179.6959	169.361	0	4161.645
weeklypay109	10377	180.2937	195.9793	0	8853.75
weeklypay110	10377	179.4982	171.0615	0	4431.781
weeklypay111	10377	179.9395	179.1373	0	7231.481
weeklypay112	10377	179.4784	171.6661	0	4914.846
weeklypay113	10377	180.4206	179.9583	0	5210.872
weeklypay114	10377	180.2529	180.6438	0	7021.146
weeklypay115	10377	180.8825	169.7268	0	3399.286
weeklypay116	10377	180.7978	166.7503	0	3913.862
weeklypay117	10377	179.7282	164.3365	0	3964.662
weeklypay118	10377	179.8739	162.741	0	2712.52
weeklypay119	10377	180.6972	174.3128	0	5955.543
weeklypay120	10377	181.3649	175.3526	0	5543.543
weeklypay121	10377	181.089	170.8102	0	4059.376
weeklypay122	10377	180.9149	166.4539	0	3663.014
weeklypay123	10377	182.2959	173.8364	0	4736.429
weeklypay124	10377	182.8207	176.1538	0	4533.263
weeklypay125	10377	182.5226	189.5014	0	6983.413
weeklypay126	10377	180.9286	162.7812	0	2461.71
weeklypay127	10377	181.6691	162.874	0	3725.211
weeklypay128	10377	181.1002	160.7474	0	2820.759
weeklypay129	10377	181.5227	165.2896	0	3673.046
weeklypay130	10377	180.0482	154.0649	0	1656.203

A.2.3 Summary Statistics for Weekly Pay – Frequent Support Group

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay1	9972	115.1964	155.9499	0	3863.533
weeklypay2	9972	115.7275	158.3328	0	3733.416
weeklypay3	9972	116.5204	163.368	0	4065.952
weeklypay4	9972	115.9254	166.1427	0	5326.286
weeklypay5	9972	115.9618	163.5517	0	4065.952
weeklypay6	9972	116.5105	170.1057	0	3754.593
weeklypay7	9972	115.9402	173.7635	0	7305.339
weeklypay8	9972	114.5037	154.5134	0	3204.814
weeklypay9	9972	115.6981	173.9033	0	7816.823
weeklypay10	9972	116.8082	170.0753	0	5902.217
weeklypay11	9972	116.8826	170.3292	0	5961.799
weeklypay12	9972	115.757	162.7126	0	4610.331
weeklypay13	9972	114.8848	155.6632	0	3370.88
weeklypay14	9972	114.1661	154.179	0	3370.88
weeklypay15	9972	113.2631	152.3727	0	2468.04
weeklypay16	9972	112.9277	161.5024	0	6530.929
weeklypay17	9972	112.9505	148.3138	0	1894.88
weeklypay18	9972	113.0392	157.7822	0	3938.561
weeklypay19	9972	112.5032	153.0252	0	4561.893
weeklypay20	9972	112.3971	156.8812	0	4561.893
weeklypay21	9972	112.5153	152.6256	0	4561.893
weeklypay22	9972	112.7711	152.6073	0	4613.727
weeklypay23	9972	113.9455	175.3617	0	8623.631
weeklypay24	9972	114.6906	184.3713	0	6825.85
weeklypay25	9972	112.4084	160.9729	0	5685.418
weeklypay26	9972	111.755	150.3323	0	3467.731
weeklypay27	9972	111.9285	154.1957	0	4841.234
weeklypay28	9972	112.5187	178.397	0	8248.094
weeklypay29	9972	111.7411	172.4393	0	7071.543
weeklypay30	9972	111.8044	170.5301	0	7170.382
weeklypay31	9972	110.6837	142.9349	0	3888.455
weeklypay32	9972	109.4413	139.6411	0	3332.961
weeklypay33	9972	109.9065	150.8084	0	6654.443

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay34	9972	109.3362	137.9818	0	2815.632
weeklypay35	9972	109.5889	136.617	0	1970.98
weeklypay36	9972	108.7909	133.5105	0	2592
weeklypay37	9972	108.9018	131.5502	0	2406.668
weeklypay38	9972	108.7346	137.7296	0	5191.233
weeklypay39	9972	109.3372	135.6219	0	3450.504
weeklypay40	9972	109.089	136.2492	0	4825.581
weeklypay41	9972	109.0946	131.592	0	4825.581
weeklypay42	9972	109.8907	128.6121	0	4825.581
weeklypay43	9972	112.0868	139.2236	0	4913.486
weeklypay44	9972	112.8739	134.1298	0	6754.963
weeklypay45	9972	114.9289	118.644	0	3346.025
weeklypay46	9972	118.4766	124.262	0	4424.007
weeklypay47	9972	122.0591	121.785	0	4505.16
weeklypay48	9972	126.2709	133.9339	0	5325.383
weeklypay49	9972	131.9592	125.0561	0	6044.334
weeklypay50	9972	136.503	111.5161	0	6042.536
weeklypay51	9972	141.434	115.3364	0	6041.187
weeklypay52	9972	146.9044	105.4335	0	5191.647
weeklypay53	9972	161.7542	92.22863	1.451429	947.2897
weeklypay54	9972	159.5768	95.62015	0	1458.987
weeklypay55	9972	159.8133	99.4916	0	1458.987
weeklypay56	9972	159.9031	103.2015	0	2102.998
weeklypay57	9972	160.1485	115.6191	0	4846.949
weeklypay58	9972	160.4384	112.9726	0	2570.714
weeklypay59	9972	160.9467	120.8373	0	4718.249
weeklypay60	9972	161.9625	132.6659	0	6288.55
weeklypay61	9972	161.7672	118.9502	0	2088.428
weeklypay62	9972	161.3546	120.061	0	2784.572
weeklypay63	9972	162.2333	123.3903	0	2876.052
weeklypay64	9972	162.0689	122.2853	0	2157.039
weeklypay65	9972	163.7857	128.8969	0	4285.714
weeklypay66	9972	163.7572	128.4837	0	3214.286
weeklypay67	9972	162.6831	127.6972	0	2965.3
weeklypay68	9972	163.6015	132.9507	0	4523.103

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay69	9972	164.3826	138.1989	0	4594.769
weeklypay70	9972	164.9716	149.2251	0	6397.097
weeklypay71	9972	164.8598	134.2805	0	2440.151
weeklypay72	9972	165.7521	144.9444	0	5439.25
weeklypay73	9972	166.9651	154.9472	0	7574.53
weeklypay74	9972	167.3456	141.1079	0	2572.887
weeklypay75	9972	167.3171	139.5287	0	2142.857
weeklypay76	9972	168.4446	153.1236	0	5426.297
weeklypay77	9972	168.9381	149.0357	0	4550.954
weeklypay78	9972	171.1399	163.1767	0	4688.279
weeklypay79	9972	170.907	159.0765	0	4200.028
weeklypay80	9972	171.4552	164.7614	0	4808.571
weeklypay81	9972	172.2152	163.2758	0	4605.953
weeklypay82	9972	173.9359	169.0238	0	4237.219
weeklypay83	9972	175.2187	171.1761	0	4109.433
weeklypay84	9972	174.2048	194.5198	0	9221.197
weeklypay85	9972	175.5634	228.4233	0	8852.027
weeklypay86	9972	174.2529	188.8669	0	6167.923
weeklypay87	9972	174.3752	187.2767	0	7317.104
weeklypay88	9972	174.3696	200.5153	0	8514.929
weeklypay89	9972	173.0202	164.0499	0	3747.604
weeklypay90	9972	173.0678	172.4406	0	5201.049
weeklypay91	9972	171.5777	153.9638	0	2868.964
weeklypay92	9972	172.0693	163.2571	0	4177.093
weeklypay93	9972	171.9629	165.0045	0	4473.764
weeklypay94	9972	174.0153	185.3882	0	5871.114
weeklypay95	9972	172.5729	158.7666	0	2652.445
weeklypay96	9972	172.9744	160.3205	0	3982.716
weeklypay97	9972	173.2428	154.1897	0	2654.792
weeklypay98	9972	173.669	161.4053	0	5514.526
weeklypay99	9972	174.9007	168.5542	0	4257.504
weeklypay100	9972	175.9102	179.4998	0	7987.964
weeklypay101	9972	176.3447	194.8028	0	7670.206
weeklypay102	9972	175.2933	178.2086	0	5092.163
weeklypay103	9972	174.8856	169.602	0	5526.486

Week No	Obs	Mean	Std. Dev.	Min	Max
weeklypay104	9972	175.9378	181.8613	0	6588.944
weeklypay105	9972	175.4253	155.9351	0	2411.021
weeklypay106	9972	177.3917	169.5997	0	3884.267
weeklypay107	9972	178.9182	178.2171	0	5211.446
weeklypay108	9972	178.6497	166.982	0	3509.448
weeklypay109	9972	178.6604	175.0933	0	4892.864
weeklypay110	9972	178.3383	192.6817	0	9217.564
weeklypay111	9972	177.7194	172.6564	0	6941.906
weeklypay112	9972	178.44	175.4626	0	5400.15
weeklypay113	9972	178.2503	159.777	0	2633.008
weeklypay114	9972	180.3865	194.0509	0	7394.983
weeklypay115	9972	179.8679	163.301	0	2961.369
weeklypay116	9972	180.0513	163.8613	0	3337.822
weeklypay117	9972	180.1337	165.4717	0	3971.379
weeklypay118	9972	179.2906	180.8281	0	8962.88
weeklypay119	9972	178.5613	167.0448	0	5891.61
weeklypay120	9972	179.2113	167.4282	0	3177.165
weeklypay121	9972	178.7315	160.2654	0	2336.666
weeklypay122	9972	180.404	172.9471	0	5192.667
weeklypay123	9972	181.0213	174.7925	0	6774.701
weeklypay124	9972	180.8269	162.4378	0	3135.099
weeklypay125	9972	182.1694	184.6666	0	6554.501
weeklypay126	9972	180.8867	163.1892	0	3501.819
weeklypay127	9972	181.5943	186.1112	0	6876.279
weeklypay128	9972	179.8532	160.1762	0	2832.793
weeklypay129	9972	180.4588	163.8503	0	4000.697
weeklypay130	9972	179.3597	153.03	0	1230.242

A.2.4 Summary Statistics and Sample Sizes - IWP Treatment Groups.

Sample Sizes - IWP Treatment Groups

	Minimal	Moderate	Frequent	Total
All Claimants	11,107	10,377	9,972	31,456
Full Service	4,081	3,731	3,619	11,431
Live Service	7,026	6,646	6,353	20,025
Male	4,681	4,368	4,271	13,320
Female	6,426	6,009	5,701	18,136
Has Partner	1,919	1,874	1,736	5,529
No Partner	9,188	8,503	8,236	25,927
Has Partner on Trial	490	453	460	1,403
No Partner on Trial	10,617	9,924	9,512	30,053
North East	1,468	1,299	1,218	3,985
North West	3,186	2,970	2,833	8,989
London	2,341	2,158	2,090	6,589
Southern	1,597	1,387	1,339	4,323
Central	1,424	1,540	1,467	4,431
Wales	326	299	319	944
Scotland	765	724	706	2,195

Sample Sizes for Age Cohorts across IWP Treatment Groups

Treatment	18-25	26-35	36-45	46-55	56-65	Total
Minimal	1,955	3,174	2,215	2,390	1,373	11,107
Moderate	1,638	2,900	2,114	2,383	1,342	10,377
Frequent	1,649	2,812	2,018	2,244	1,249	9,972
Total	5,242	8,886	6,347	7,017	3,964	31,456

A.2.5 Result of Test for Parallel Trends in Pre-Trial Period - Frequent & Moderate Support vs Minimal Support Group.

Moderate vs Minimal Support Group

Number of obs = 1117168
F(3,1117164) = 0.70
Prob >F = 0.5541
R-squared = 0.0000
Root MSE = 143.13

		Robust			
weeklypay	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**
t	0.0522961	1.47318	0.04	0.972	-2.835087 2.939679
treatment2	-1.3807	2.183816	-0.63	0.527	-5.660905 2.899505
did2	1.671414	2.200782	0.76	0.448	-2.642044 5.984871
_cons	115.1522	1.460595	78.84	0	112.2895 118.0149

Frequent vs Minimal Support Group

Number of obs = 1096108
F(3,1096104) = 0.14
Prob >F = 0.9358
R-squared = 0.0000
Root MSE = 147.44

		Robust			
weeklypay	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**
t	0.0522961	1.47318	0.04	0.972	-2.835087 2.93968
treatment3	0.0442263	2.138216	0.02	0.983	-4.146605 4.235058
did3	0.1382661	2.157141	0.06	0.949	-4.089657 4.366189
_cons	115.1522	1.460595	78.84	0	112.2895 118.0149

A.2.6 Result of Test for Parallel Trends across Quantiles in Pre-Trial Period - Moderate vs Minimal Support Group.

		Bootstrap				
weeklypay	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf.**	**Interval]**
q10						
t	(dropped)					
treatment2	(dropped)					
did2	(dropped)					
_cons	(dropped)					
q20						
t	(dropped)					
treatment2	(dropped)					
did2	(dropped)					
_cons	(dropped)					
q30						
t	(dropped)					
treatment2	(dropped)					
did2	(dropped)					
_cons	(dropped)					
q40						
t	38.69286	0.4298908	90.01	0	37.85028	39.53543
treatment2	2.69E-09	9.31E-10	2.89	0.004	8.64E-10	4.51E-09
did2	1.507145	0.6273638	2.4	0.016	0.277533	2.736757
_cons	-2.09E-09	8.01E-10	-2.62	0.009	-3.66E-09	-5.25E-10
q50						
t	23.61333	3.249717	7.27	0	17.24399	29.98266
treatment2	-5.94656	5.974549	-1	0.32	-17.6565	5.763354
did2	7.46323	5.894321	1.27	0.205	-4.08944	19.0159
_cons	65.87	3.210653	20.52	0	59.57723	72.16277
q60						
t	7.933334	2.137098	3.71	0	3.744695	12.12197
treatment2	-1.27207	3.068484	-0.41	0.678	-7.2862	4.742053
did2	3.647308	2.91332	1.25	0.211	-2.0627	9.357317
_cons	113.4	2.159808	52.5	0	109.1669	117.6332
q70						
t	-3.02858	1.418658	-2.13	0.033	-5.8091	-0.24806
treatment2	-0.69429	2.683695	-0.26	0.796	-5.95424	4.565661
did2	1.663574	2.547333	0.65	0.514	-3.32911	6.656261
_cons	163.1943	1.511288	107.98	0	160.2322	166.1564
q80						
t	-17	1.906489	-8.92	0	-20.7367	-13.2634
treatment2	-4.02286	3.160226	-1.27	0.203	-10.2168	2.171078
did2	4.652863	3.137826	1.48	0.138	-1.49717	10.80289
_cons	225	1.863779	120.72	0	221.3471	228.6529
q90						
t	-22.0725	2.047597	-10.78	0	-26.0857	-18.0593
treatment2	1.154633	3.769688	0.31	0.759	-6.23383	8.543094
did2	-1.45462	3.796594	-0.38	0.702	-8.89582	5.986575
_cons	302.8725	2.044097	148.17	0	298.8661	306.8789

A.2.7 Result of Test for Parallel Trends across Quantiles in Pre-Trial Period - Frequent vs Minimal Support Group.

		Bootstrap				
weeklypay	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf.**	**Interval]**
q10						
t	(dropped)					
treatment3	(dropped)					
did3	(dropped)					
_cons	(dropped)					
q20						
t	(dropped)					
treatment3	(dropped)					
did3	(dropped)					
_cons	(dropped)					
q30						
t	(dropped)					
treatment3	(dropped)					
did3	(dropped)					
_cons	(dropped)					
q40						
t	38.69286	0.473148	81.78	0	37.7655	39.62021
treatment3	1.22E-09	1.22E-09	1	0.317	-1.17E-09	3.62E-09
did3	1.421429	0.858161	1.66	0.098	-0.26054	3.103395
_cons	-4.13E-11	9.21E-10	-0.04	0.964	-1.85E-09	1.76E-09
q50						
t	23.61333	2.135861	11.06	0	19.42711	27.79954
treatment3	-1.05483	4.818735	-0.22	0.827	-10.4994	8.389724
did3	1.91436	4.702377	0.41	0.684	-7.30214	11.13086
_cons	65.87	2.226983	29.58	0	61.50519	70.23481
q60						
t	7.933334	2.027856	3.91	0	3.958806	11.90786
treatment3	-1.232	3.241817	-0.38	0.704	-7.58585	5.12185
did3	1.253502	3.072405	0.41	0.683	-4.76831	7.275311
_cons	113.4	2.088765	54.29	0	109.3061	117.4939
q70						
t	-3.02858	1.695488	-1.79	0.074	-6.35168	0.294519
treatment3	-2.39429	2.969973	-0.81	0.42	-8.21533	3.426759
did3	1.65715	2.853718	0.58	0.561	-3.93604	7.250341
_cons	163.1943	1.731311	94.26	0	159.801	166.5876
q80						
t	-17	1.589541	-10.69	0	-20.1155	-13.8846
treatment3	-0.01276	3.084045	0	0.997	-6.05738	6.031867
did3	-1.20152	2.963416	-0.41	0.685	-7.00972	4.606672
_cons	225	1.688983	133.22	0	221.6897	228.3103
q90						
t	-22.0725	2.027855	-10.88	0	-26.047	-18.098
treatment3	0.969513	3.556737	0.27	0.785	-6.00157	7.940598
did3	-4.56949	3.722799	-1.23	0.22	-11.8661	2.727072
_cons	302.8725	1.979069	153.04	0	298.9936	306.7514

A.2.8 Summary of Regression Results

Quantile Treatment Effects - Moderate & Frequent Support Groups

Minimal vs Moderate			
Quantile	Moderate	Std Err	P>|t|
0.4	2.831242	0.76212	0.0001
0.5	2.657333	0.5201575	0.0001
0.6	1.899277	0.3829933	0.0001
0.7	3.081162	0.4626118	0.0001
0.8	4.200653	0.5763492	0.0001
0.9	3.281464	0.6523328	0.0001
Mean Estimate	3.909369	0.3745575	0.0001
No of Observations - 2792920			
Minimal vs Frequent			
Quantile	Frequent	Std Err	P>|t|
0.4	2.418907	0.8161139	0.003
0.5	2.626289	0.4672275	0.0001
0.6	3.635712	0.4427722	0.0001
0.7	3.36171	0.5097878	0.0001
0.8	2.835571	0.7347352	0.0001
0.9	3.758881	1.110726	0.001
Mean Estimate	2.543322	0.3825184	0.0001
No of Observations - 2740270			

Quantile Treatment Effects - Males vs Females

Minimal vs Moderate (Males Only)			
Quantile	**Males**	**Std Err**	**P>|t|**
0.4	2.197835	1.549403	0.156
0.5	3.578606	0.6723124	0.000
0.6	3.142311	0.4830655	0.000
0.7	3.368835	0.6503025	0.000
0.8	1.612854	0.7445642	0.030
0.9	2.765472	1.028816	0.007
Mean Estimate	2.783	0.642	0.000
No of Observations - 1176370			
Minimal vs Moderate (Females Only)			
Quantile	**Female**	**Std Err**	**P>|t|**
0.4	1.294998	0.6437798	0.044
0.5	1.513138	0.4779653	0.002
0.6	1.68409	0.4531153	0.000
0.7	3.529221	0.6665291	0.000
0.8	4.831299	0.7387546	0.000
0.9	7.049164	1.04031	0.000
Mean Estimate	4.737	0.447	0.000
No of Observations - 1616550			
Minimal vs Frequent (Males Only)			
Quantile	**Male**	**Std Err**	**P>|t|**
0.4	-2.52576	1.533536	0.100
0.5	0.0207367	0.826341	0.980
0.6	-1.44265	0.7040157	0.040
0.7	-1.995453	0.5121342	0.000
0.8	0.6860504	1.01729	0.500
0.9	-0.7273865	1.150505	0.527
Mean Estimate	-0.94	0.656	0.152
No of Observations - 1163760			
Minimal vs Frequent (Females Only)			
Quantile	**Female**	**Std Err**	**P>|t|**
0.4	2.762035	0.899512	0.002
0.5	3.721367	0.5971509	0.000
0.6	5.640114	0.6081183	0.000
0.7	6.795303	0.5722459	0.000
0.8	6.043289	0.8100019	0.000
0.9	7.46637	1.142553	0.000
Mean Estimate	5.023	0.454	0.000
No of Observations - 1576510			

Quantile Treatment Effects - Live-Service vs Full-Service

Minimal vs Moderate (Live-Service)			
Quantile	**Live-Service**	**Std Err**	**P>|t|**
0.4	3.340355	0.2842379	0.000
0.5	-0.4810181	0.6466755	0.457
0.6	0.5001297	0.5184708	0.335
0.7	-1.352341	0.511608	0.008
0.8	-2.084305	0.8769112	0.017
0.9	-3.745422	0.9714233	0.000
Mean Estimate	1.051	0.446	0.019
No of Observations - 1777360			
Minimal vs Moderate (Full-Service)			
Quantile	**Full-Service**	**Std Err**	**P>|t|**
0.4	5.214325	0.9226558	0.000
0.5	4.249039	0.6384985	0.000
0.6	7.055634	0.5671179	0.000
0.7	8.463547	0.7462776	0.000
0.8	12.53259	1.190005	0.000
0.9	18.45007	1.679774	0.000
Mean Estimate	8.245	0.663	0.000
No of Observations - 1015560			
Minimal vs Frequent (Live-Service)			
Quantile	**Live-Service**	**Std Err**	**P>|t|**
0.4	3.181	0.3090086	0.000
0.5	2.381565	0.7935121	0.003
0.6	3.133705	0.3904935	0.000
0.7	3.115204	0.4396333	0.000
0.8	3.351425	0.6529645	0.000
0.9	3.987244	1.08914	0.000
Mean Estimate	3.02	0.456	0.000
No of Observations - 1739270			
Minimal vs Frequent (Full-Service)			
Quantile	**Full-Service**	**Std Err**	**P>|t|**
0.4	2.17823	0.7964449	0.006
0.5	2.07914	0.8639517	0.016
0.6	3.949615	0.5519689	0.000
0.7	0.8210144	0.7028809	0.243
0.8	2.83989	0.9762051	0.004
0.9	3.383057	1.179045	0.004
Mean Estimate	1.278	0.675	0.058
No of Observations - 1001000			

Average Treatment Effects - Age Cohorts

Minimal vs Moderate				
Age Cohort	Moderate	Std Err	P>|t|	No of Observations
Age 18-25	3.236	0.76	0.000	467090
Age 26-35	-0.353	0.665	0.596	789620
Age 36-45	5.94	0.834	0.000	562770
Age 46-55	9.852	0.817	0.000	620490
Age 56-65	6.69	1.286	0.000	352950
Minimal vs Frequent				
Age Cohort	**Frequent**	**Std Err**	**P>|t|**	**No of Observations**
Age 18-25	6.223	0.763	0.000	468520
Age 26-35	1.213	0.682	0.075	778180
Age 36-45	8.325	0.848	0.000	550290
Age 46-55	1.441	0.836	0.085	602420
Age 56-65	-2.769	1.334	0.038	340860

Average Treatment Effects - Regions

Minimal vs Moderate				
Region	Moderate	Std Err	P>|t|	No of Observations
Wales	12.421	2.048	0.000	81250
North West	8.933	0.626	0.000	800280
Southern	7.185	1.011	0.000	387920
North East	6.142	1.111	0.000	359710
Scotland	0.377	1.455	0.796	193570
LHC	-1.439	0.879	0.102	584870
Central	-3.223	1.024	0.002	385320
Minimal vs Frequent				
Region	**Frequent**	**Std Err**	**P>|t|**	**No of Observations**
Wales	23.688	2.046	0.000	83850
North West	5.667	0.632	0.000	782470
Southern	1.907	1.056	0.071	381680
North East	1.328	1.136	0.242	349180
Scotland	7.087	1.471	0.000	191230
LHC	-2.019	0.895	0.024	576030
Central	-2.495	1.053	0.018	375830

Quantile Treatment Effects - Women Above & Below Age 35

Females aged over 35 - Minimal vs Moderate			
Quantile	**Age over 35**	**Std Err**	**P>|t|**
0.4	7.848572	0.549	0.000
0.5	6.382172	0.540246	0.000
0.6	6.113205	0.568147	0.000
0.7	9.509781	0.571998	0.000
0.8	9.843216	0.686712	0.000
0.9	12.8299	0.929668	0.000
Mean Estimate	9.075	0.612	0.000
No of Observations - 960570			
Females aged below 36 - Minimal vs Moderate			
Quantile	**Age below 36**	**Std Err**	**P>|t|**
0.4	-0.3186679	2.314212	0.890
0.5	-4.484962	0.946372	0.000
0.6	-3.202805	0.552479	0.000
0.7	-3.387497	0.790508	0.000
0.8	-0.1134949	1.122381	0.919
0.9	1.240158	1.360034	0.362
Mean Estimate	-0.311	0.634	0.623
No of Observations - 655980			
Females aged over 35 - Minimal vs Frequent			
Quantile	**Age over 35**	**Std Err**	**P>|t|**
0.4	4.796959	0.950474	0.000
0.5	5.351852	0.722273	0.000
0.6	6.209946	0.695598	0.000
0.7	7.793594	0.538074	0.000
0.8	5.721619	0.726888	0.000
0.9	8.395508	1.078687	0.000
Mean Estimate	6.227	0.626	0.000
No of Observations - 920400			
Females aged below 36 - Minimal vs Frequent			
Quantile	**Age below 36**	**Std Err**	**P>|t|**
0.4	9.230921	2.872392	0.001
0.5	1.600021	0.882959	0.070
0.6	4.582741	0.709539	0.000
0.7	6.403252	0.871295	0.000
0.8	8.812622	1.240759	0.000
0.9	8.474823	1.619226	0.000
Mean Estimate	4.026	0.641	0.000
No of Observations - 656110			

Average Treatment Effects - Women Above & Below Age 35 - Regions

Females over Age 35 - Moderate Support - Regions				
	Moderate	**Std Err**	**P>|t|**	**No of Observations**
Southern	18.101	1.609	0.000	137150
North West	14.944	1.038	0.000	283400
North East	14.319	1.799	0.000	114790
LHC	5.483	1.374	0.000	217230
Scotland	4.9	2.818	0.082	53040
Wales	2.819	3.928	0.473	19890
Central	-8.244	1.637	0.000	135070
Females over Age 35 - Frequent Support - Regions				
	Frequent	**Std Err**	**P>|t|**	**No of Observations**
Southern	2.24	1.698	0.187	132080
North West	4.283	1.046	0.000	267670
North East	10.89	1.807	0.000	111930
LHC	11.646	1.363	0.000	214890
Scotland	8.365	2.791	0.003	51740
Wales	10.937	4.307	0.011	18850
Central	-2.119	1.776	0.233	123240

A.3 Appendix to Chapter-4

A.3.1 Tabulation of Time Dummies

Specification of Time Dummies used for Regressions

	Weeks Investigated						
Time Dummy	**1-52**	**53-65**	**66-78**	**79-91**	**92-104**	**105-117**	**118-130**
$\mathbf{T}$	0	1	1	1	1	1	1
$\mathbf{T_1}$	0	1	0	0	0	0	0
$\mathbf{T_2}$	0	0	1	0	0	0	0
$\mathbf{T_3}$	0	0	0	1	0	0	0
$\mathbf{T_4}$	0	0	0	0	1	0	0
$\mathbf{T_5}$	0	0	0	0	0	1	0
$\mathbf{T_6}$	0	0	0	0	0	0	1

A.3.2 Results of Investigation of Treatment Effects over Time

Investigation of IWP Treatment Effects over Time
Moderate & Frequent Support Groups

Minimal vs Moderate			
Week No	**Moderate**	**Std Err**	**P>|t|**
Week 53-65	1.410126	1.434204	0.326
Week 66-78	1.841977	1.679199	0.273
Week 79-91	4.302487	1.851303	0.02
Week 92-104	5.783474	1.949058	0.003
Week 105-117	5.834774	1.991858	0.003
Week 118-130	4.283374	2.027169	0.035
No of Observations - 2792920			
Minimal vs Frequent			
Week No	**Frequent**	**Std Err**	**P>|t|**
Week 53-65	-0.1189959	1.465386	0.935
Week 66-78	1.165923	1.734768	0.502
Week 79-91	3.232229	1.910718	0.091
Week 92-104	3.225682	1.973333	0.102
Week 105-117	4.506753	2.021928	0.026
Week 118-130	3.248343	2.060635	0.115
No of Observations - 2740270			

Investigation of IWP Treatment Effects over Time

Male vs Female

Minimal vs Moderate - Males			
Week No	**Males**	**Std Err**	**P>|t|**
Week 53-65	0.2592653	2.521964	0.918
Week 66-78	0.0157854	2.870592	0.996
Week 79-91	4.626315	3.163767	0.144
Week 92-104	3.802824	3.298456	0.249
Week 105-117	5.337817	3.431509	0.12
Week 118-130	2.65864	3.517768	0.45
No of Observations - 1176370			
Minimal vs Moderate - Females			
Week No	**Female**	**Std Err**	**P>|t|**
Week 53-65	2.253586	1.663071	0.175
Week 66-78	3.177069	2.011661	0.114
Week 79-91	4.075353	2.217691	0.066
Week 92-104	7.232786	2.359465	0.002
Week 105-117	6.207107	2.363948	0.009
Week 118-130	5.479014	2.38396	0.022
No of Observations - 1616550			
Minimal vs Frequent - Males			
Week No	**Male**	**Std Err**	**P>|t|**
Week 53-65	-4.596458	2.567726	0.073
Week 66-78	-3.210018	2.970193	0.28
Week 79-91	0.937279	3.264742	0.774
Week 92-104	1.068006	3.379574	0.752
Week 105-117	1.292431	3.462148	0.709
Week 118-130	-1.13226	3.565311	0.751
No of Observations - 1163760			
Minimal vs Frequent - Females			
Week No	**Female**	**Std Err**	**P>|t|**
Week 53-65	3.142533	1.700224	0.065
Week 66-78	4.341596	2.067715	0.036
Week 79-91	4.840204	2.282436	0.034
Week 92-104	4.713305	2.350615	0.045
Week 105-117	6.765343	2.4095	0.005
Week 118-130	6.33329	2.424659	0.009
No of Observations - 1576510			

Investigation of IWP Treatment Effects over Time

Live-Service vs Full-Service

Minimal vs Moderate - Live-Service			
Week No	**Live-Service**	**Std Err**	**P>|t|**
Week 53-65	-1.601701	1.631915	0.326
Week 66-78	-1.090865	1.987185	0.583
Week 79-91	1.488976	2.219184	0.502
Week 92-104	2.122953	2.319017	0.36
Week 105-117	3.518616	2.383492	0.14
Week 118-130	1.866503	2.449744	0.446
No of Observations - 1777360			
Minimal vs Moderate - Full-Service			
Week No	**Full-Service**	**Std Err**	**P>|t|**
Week 53-65	6.042798	2.667212	0.024
Week 66-78	6.381669	2.997659	0.033
Week 79-91	8.624421	3.253782	0.008
Week 92-104	11.55295	3.461923	0.001
Week 105-117	9.142257	3.494787	0.009
Week 118-130	7.725934	3.50041	0.027
No of Observations - 1015560			
Minimal vs Frequent - Live-Service			
Week No	**Live-Service**	**Std Err**	**P>|t|**
Week 53-65	0.1592196	1.666362	0.924
Week 66-78	0.4809696	2.035445	0.813
Week 79-91	4.121976	2.303514	0.074
Week 92-104	4.876899	2.374869	0.04
Week 105-117	4.822032	2.416891	0.046
Week 118-130	3.658577	2.486831	0.141
No of Observations - 1739270			
Minimal vs Frequent - Full-Service			
Week No	**Full-Service**	**Std Err**	**P>|t|**
Week 53-65	-1.022542	2.707241	0.706
Week 66-78	1.980232	3.122146	0.526
Week 79-91	1.279274	3.313909	0.699
Week 92-104	-0.0987157	3.421141	0.977
Week 105-117	3.48939	3.53894	0.324
Week 118-130	2.039162	3.551264	0.566
No of Observations - 1001000			

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