# The Impact of Time and Risk Preferences and Health Behaviour on Adherence to Guidelines for the Management of Type 2 Diabetes (T2DM): Findings from the English Longitudinal Study of Ageing (ELSA)

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The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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## Abstract

Regular monitoring of key risk factors and lifestyle changes are at the centre of national and international guidelines on T2DM management. However, despite the clear benefit, adherence to these guidelines is often difficult to achieve by the people living with T2DM. This thesis explores the role of time and risk preferences in explaining such behaviour and the associated costs and quality of life implications. Three empirical analyses will be conducted to gain insights into adherence to T2DM-related management behaviour. The first analysis investigates the relationship between time and risk preferences, and adherence to annual routine medical checks for T2DM management. The second analysis quantifies the impact of different time and risk preference rates on the long-term health outcomes and costs of T2DM patients. The third analysis examines whether a new T2DM diagnosis can trigger behaviour change in newly diagnosed individuals. The findings reveal that heterogeneity in individuals' levels of time and risk preferences was not associated with adherence to the annual care processes recommended by the guidelines for T2DM management. Similarly, preferences did not explain the difference in T2DM related health outcomes and costs. The final analysis found limited evidence of behaviour change following a T2DM diagnosis apart from a reduction in smoking. Healthcare providers are advised to regularly assess patients' willingness and ability to comply with the T2DM guidelines and manage treatment accordingly as a way to improve adherence to T2DM management guidelines.

# Table of Contents

# List of Figures

# List of Tables

## Abbreviation

**T2DM - Type 2 Diabetes Mellitus**

**ELSA - English Longitudinal Study of Ageing**

**UKPDS OM2 - United Kingdom Prospective Diabetes Study Outcome Model 2**

**TRP - Time and Risk Preferences**

**CVD - cardiovascular disease**

**BMI - Body Mass Index**

**NICE - The National Institute for Health and Care Excellence**

**UK - United Kingdom**

**NAO - National Diabetes Audit**

**OR - Odds Ratio**

**CI - Confidence Interval**

**CRRA - Coefficient Relative Risk Aversion**

**MI - Myocardial Infarction**

**GP - General Practitioner**

**DPP - Diabetes Prevention Programme**

**QOF - Quality Outcomes Framework**

**HTA-Health Technology Assessment**

**ADA - American Diabetes Association**

**QALY - Quality Adjusted Life Years**

**ISPOR - The Professional Society for Health Economics and Outcomes Research**

**DSA - Deterministic Sensitivity Analysis**

**PSA - Probabilistic Sensitivity Analysis**

**CHD - coronary heart disease**

**IHD - Ischemic Heart Disease**

**EQ-5D - EuroQol 5 Dimension - a Measure for Health-Related Quality of Life**

**WBC - White Blood Cells Count**

**eGFR - Estimated Glomerular Filtration Rate**

**HDL - High-Density Lipoprotein**

**LDL - Low Density Lipoprotein**

**HbA1c - Glycated Haemoglobin**

**QALE - Quality Adjusted Life Years**

**SD - Standard Deviation**

**HTP - High Time Preferences**

**MNAR - Missing Not at Random**

**MAR - Missing at Random**

**HRS - Health and Retirement Survey**

**GEE - Generalized Estimating Equation**

**RE - Random Effect**

**PSM - Propensity Score Matching**

**OLS - Ordinary Least Square**

# Chapter 1
# Introduction

## 1.1 Background

Diabetes is a chronic, progressive metabolic disorder in which the body fails to maintain a normal condition of glucose homeostasis [1, 2]. Glucose homeostasis is the process by which the body retains the plasma glucose concentration within a tolerable range. The inability of the pancreas to produce enough insulin or the incapacity of the cells to absorb it properly leads to hyperglycaemia, an excess of glucose in the bloodstream. Chronic hyperglycaemia resulting from diabetes is one of the leading causes of micro-vascular and macro-vascular complications, such as nerve damage, kidney problems, and various cardiovascular diseases.

There are two primary types of diabetes [3]: on the one hand, Type 1 diabetes occurs whenever the cells entitled to produce insulin are unable to work correctly and produce no insulin. This condition is also known as insulin-dependent diabetes. On the other hand, Type 2 diabetes mellitus (T2DM) develops when the insulin-producing cells cannot produce enough insulin or fail to use it efficiently (known as insulin resistance). The vast majority of the total cases of diabetes (90%) refers to T2DM.

While type 1 diabetes is an autoimmune condition, and as such, it entails a predominantly genetic component, the causes of type 2 diabetes are generally multifactorial. They include, among others, obesity, conducting a sedentary lifestyle and following an unhealthy diet. These are modifiable risk factors, as they are, albeit partially, under the control of individuals.

Worldwide figures about the prevalence of diabetes are alarming, and as stated by different authoritative sources, we are currently experiencing what can be

referred to as a “global epidemic” [4]. According to the World Health Organization [5], 422 million people across the globe are currently living with T2DM, and these numbers have more than tripled compared to the year 1980 when the global prevalence of diabetes was 108 million. These figures make T2DM one of the fastest-growing health challenges of the century. Furthermore, projections from the International Diabetes Federation (IDF) report [6] found that globally, the total number of adults with diabetes will hit 642 million by 2040. Moreover, these projections are likely underestimated since they do not account for undiagnosed cases.

The presence of T2DM can be detrimental on patient’s health related quality of life (HRQoL) [7]. The long terms complications of T2DM include retinopathy which may cause potential loss of vision; nephropathy which may lead to renal failure in the long term and peripheral neuropathy with its associated risk of foot ulcer, the leading cause of feet amputation. Results from the United Kingdom Perspective Diabetes Study [8], showed that people who experienced T2DM related complication over the last year had worse quality of life, as measured by the EQ5D (a generic quality of life measure), than those without complications with median scores of 0.73 and 0.83 respectively ($p<0.0012$). Estimates from a study that utilised data from the Framingham Heart Study suggested that men and women aged 50 years or older living with T2DM had, on average, 7.5 and 8.2 years lower life expectancy compared to the people who were not affected by the condition [9].

In addition to the dramatic impact on the affected individual’s health, T2DM bears considerable economic consequences. Worldwide figures estimate that health expenditure related to T2DM is more than $ 760 billion [10]. Once again, these figures are likely to be underestimated as they do not consider the cases of

undiagnosed diabetes [11]. In England and Wales alone, over 3.2 million adults were diagnosed with T2DM in 2013, with a 6% and 6.7% prevalence, respectively. T2DM accounts for 10% of the National Health Service (NHS) budget for England and Wales [12].

It is worth highlighting that Type 2 Diabetes is a condition in which patients typically provide a large proportion of their care by managing those above-mentioned (modifiable) risk factors such as physical inactivity, obesity, and smoking. The evidence states that people with diabetes provide 95% or more of their daily care [13]. What is more, the National Institute for Health and Care Excellence in 2015 introduced a set of evidence-based guidelines for the management of T2DM in adults [14]. These guidelines provide recommendations which stress the importance of periodic blood glucose and blood pressure monitoring as well as foot surveillance. For instance, people previously diagnosed with T2DM should receive annual medical checks for each of the nine care processes suggested by the NICE Table 2.1. All the behaviour described above are crucial for optimal T2DM management and therefore the present thesis will adopt the definition of adherence to type 2 diabetes management of Khunty et al., 2019 “The extent to which a person’s behaviour (taking medication, following a diet, and/or executing lifestyle changes) corresponds with the agreed recommendations from a healthcare provider” [15].

Ongoing adherence to the guidelines for managing T2DM can significantly decrease the risk of experiencing diabetes-related complications and improve the general quality of life of the people living with the condition, as described in section 2.1 of this thesis. However, despite these guidelines being in place, individuals with T2DM do not always master adherence to T2DM guidelines [16] which often falls below the desired level [15]. According to the most updated

National Diabetes Audit report, only one in two people receives all the nine recommended care processes outlined by the NICE [17].

While non-adherence to the medical check for T2DM management is a complex challenge involving environmental factors, such as healthcare providers, among others, it partly stems from several patient-related aspects, such as motivation and knowledge about self-care procedures [16]. In search of innovative approaches to challenging uncontrolled T2DM, research suggested time and risk preferences as notable factors [18-20]. Such economic concepts have been increasingly recognised as salient in studying unhealthy behaviours such as smoking [21, 22] and physical inactivity [23, 24], including less than optimal adherence to T2DM management behaviour [25-28]. Time preferences describe how present or future-oriented an individual is [29], while risk preferences exemplify individuals' tendency to tolerate or avoid risks [30].

In light of this growing interest in the study of how time and risk preferences influence individuals' health behaviours, analysis 1 will investigate whether and to what extent individual's heterogeneity in the level of adherence to the guidelines for T2DM is attributable to differences in individuals' time and risk preferences (TRP). Furthermore, even if several papers link time and risk preferences to adherence and T2DM management strategies, less is known about the impact of differing time-and risk preference rates on T2DM long-term outcomes and costs. Hence, building upon the findings of the first analysis, analysis 2) will quantify, with the support of a detailed disease progression model designed explicitly for T2DM, how changes in TRP would eventually translate into quality-of-life improvements and costs.

Another important aspect of T2DM management, which is also linked with TRP, are health behaviours: e.g., smoking, alcohol consumption, diet, and physical activity. These are seen as an integral aspect in T2DM self-management that have been increasingly recognised as a significant contributor to adverse health consequences, including a higher risk of developing T2DM related complications [31]. Considering their importance, T2DM management guidelines [14] encourage people recently diagnosed with T2DM to adjust their behaviour towards a healthier lifestyle to keep their condition under control and avoid or delay long-term complications. However, T2DM is a silent disease sometimes characterised by a long asymptomatic period before complications manifest [6]. This delay between T2DM diagnosis and the possible occurrence of T2DM related complications can make people question the need for behaviour change [32].

Thus, analysis 3 will investigate how individuals react to the health-related information of the diagnosis of T2DM, more specifically if, as a consequence of the diagnosis itself, they are able to implement the necessary lifestyle changes recommended by the guidelines for T2DM management. It is worth mentioning that adherence to guidelines is recommended for every person living with T2DM but is particularly important for older people, where the prevalence of T2DM is much higher than in the general population [33].

These three analyses use data from the English Longitudinal Study of Ageing (ELSA)[34], a longitudinal panel survey of people living in England aged 50 or more, and appeal to the Grossman model for the Demand for Health [35] as an underlying theoretical framework. From 1.2 to 1.4, the following sections will outline how each of these three analyses has been developed and articulated, while section 1.5 will provide a brief outline of the entire thesis.

## 1.2 Analysis 1: Preference Heterogeneity and adherence to guidelines for the management of type 2 diabetes.

Intertemporal choices, defined as the relative value people assign to payoffs at different time points, are ubiquitous in economics [36]. Time is a crucial aspect of health decision-making as manifested by a rich stream of theoretical and empirical evidence linking time discounting to almost every aspect of individuals' decision-making process. Many health behaviours are linked with time discounting [20], such as smoking, over-eating, or medication non-compliance. Individuals with a high discount rate – i.e., with preferences oriented towards present gratification over more distant health benefits – have been found more likely to be obese, smokers [37], less likely to engage in some form of physical activity [23] and less prone to attending preventive medical checks [18], such as prostate screening, pap test and mammography.

Despite being two distinct concepts, time preferences are often linked to risk preferences [30]. Previous literature on the topic showed that time and risk preferences are essential components of individuals' overall attitude towards health risk [38]. Likewise, time and risk preferences have a well-established association with various health outcomes and health-related behaviour [18, 19, 22, 39-41].

Type 2 diabetes is a chronic, lifelong condition and entails a significant amount of self-care by the patients, as mentioned in section 1.1. These two aspects make time and risk preferences potentially play a role in managing the condition correctly [19, 28] and may enhance understanding of factors driving adherence

to T2DM guidelines. Therefore, the first analysis will investigate the relationship between time and risk preferences (TRP) and adherence to the medical checks suggested by the guidelines for managing T2DM. It can be hypothesised that individuals with high time preference rates i.e., more present oriented, may decide to delay gratifications, preferring more immediate payoffs compared to their low time preference rate equivalent [27, 40]. In the seminal Grossman model for the demand for health, this concept would translate into a lower propensity for individuals characterised by high time–preferences rates to invest in their health than their low time-preferences rates counterparts. Similarly, to what has been hypothesised for time preferences, it can also be postulated that individuals who exhibit higher tolerance towards risk are less prone to invest in their health compared to their more risk-averse counterparts.

The contributions of this analysis are twofold. Firstly, most of the existing literature in the field relies on proxies for measuring time and risk preferences [24, 25, 40]. Although proxies perform well in capturing individuals' preferences towards delayed gratification and attitudes towards risk in some contexts, the ELSA offers the unique opportunity to investigate the relationship between adherence and individuals' characteristics using preferences elicited from a laboratory experiment that involved incentivised lottery games [42]. Incentivised experiments have the advantage to be less subject to bias compared to non-incentivised investigations. Firstly, incentivised tasks involve real choices with concrete payoffs instead of hypothetical decisions, leading to what is known in the literature as 'hypothetical bias'. Secondly, apart possibly from one exception [27] previous studies focusing on the link between TRP and adherence to T2DM guidelines evaluated time or risk preferences individually [19, 25, 26]. Although time and risk preferences are two distinct concepts, they might be both related

with investment in health. Therefore, further research, that evaluates the impact of both time and risk preferences within the same study is warranted.

Shedding light on the relationship between time and risk preferences and adherence to the medical checks for T2DM management would enhance the understanding of factors driving non-adherence above and beyond the 'classic' socio-demographic risk factors. Findings from this research have the potential to provide crucial insights [28] into improving the long-terms outcomes of people living with T2DM, which is a topic of increasing interest.

## 1.3 Analysis 2: Preference heterogeneity and long-term outcomes of people living with type 2 diabetes.

Building upon the findings of analysis 1, analysis 2 will investigate how time and risk preferences influence the long-term outcomes (over a lifetime) of people with type 2 diabetes. This goal will be achieved using a disease progression model, namely The United Kingdom Perspective Study 2 (UKPDS-OM2) [43]. Hence if analysis 1 explored the potential association between TRP and adherence to the medical checks for T2DM management recommended by the guidelines, this further analysis will attach a specific quality of life measure (QALEs) and a monetary value to the hypothetical association described above. To the best of my knowledge, while several studies related TRP to various aspects of T2MD management [28], no previous studies investigated the impact of different TRP rates upon T2DM outcomes using a disease progression model populated with secondary data from a representative survey of the English population. In summary, this work will add to the analysis of preferences, going into more detail on how TRP may impact the quality of life and the long-term costs incurred by the people living with T2DM.

## 1.4 Analysis 3: Health investment decisions after type 2 diabetes diagnosis.

The adoption of a healthy lifestyle is paramount for optimal diabetes self-management as emphasized by T2DM guidelines [14, 44]. Individuals at high risk of developing the condition or already diagnosed with T2DM are encouraged to adopt healthier nutritional habits, quit smoking reduce sedentary behaviour and be more active. These lifestyle changes have been shown to help people with T2DM better manage their condition and reduce the risks of complications [45]. However, lifestyle changes are often difficult to achieve [32], and it is not clear whether the newly diagnosed patient changes their behaviour following a T2DM diagnosis. The evidence with this regard is abundant but shows mixed results. Changes have been detected at times, but other times individuals seem to continue with the pre-diagnosis unhealthy habits.

It can be assumed that the diagnosis of T2DM can represent a teachable moment to trigger behavioural change. Therefore, analysis 3 examines whether and to what extent individuals change their behaviour in response to T2DM diagnosis. The framework of reference will continue to be the Grossman's model of the demand for health as it will be throughout the thesis. Changing behaviour is a costly activity that requires effort for the newly diagnosed patients but can lead to better health outcomes in the long run. According to this framework, the willingness of newly diagnosed individuals to change their behaviour can be seen as an investment in health. Therefore, this work will provide a two-fold contribution to the existing literature.

On the one hand, it will link to the broader economic literature on how individuals react to 'health shocks' [46]. On the other hand, it will contribute to the previous empirical evidence investigating how individuals specifically react to T2DM diagnosis [47-49]. Still, instead of being an empirically pure work, it will fit into a specific economic framework such as the Grossman's model of the demand for health. The model predicts that individuals are willing to invest their health up to the point the marginal cost of an additional unit of investment equals the marginal benefits. A natural implication of this utility-maximising equilibrium is that purely rational individuals should counterbalance the negative health signal of T2DM diagnosis by increasing their investment in health, i.e., by implementing the necessary lifestyle changes. However, these adjustments are often challenging and not always of enough magnitude to possibly translate into sensible clinical improvements.

## 1.5 Outline of the thesis

Each chapter represents a separate analysis that a common theme will link together. As the title suggests, this theme will be adherence to medical checks for managing T2DM and more broadly T2DM self-management behaviour as defined above. As mentioned in section 1.2, Chapter 2 will explore the associations between time and risk preferences and adherence to the medical checks suggested by the National guidelines for T2DM management. Chapter 3 will develop further findings from analysis 1 by predicting how heterogeneity in individuals' time and risk preferences might impact the long-term outcomes and costs of people living with T2DM. To conclude, behaviour change is a salient aspect of good T2DM self-management strategies. Thus Chapter 4 will investigate whether people recently diagnosed with T2DM adjust their behaviour according to what is suggested by the guidelines for good T2DM management.

Finally, chapter 5 will summarise the main findings for each analysis and draw the overall conclusion from the entire work and as well as its limitations.

# Chapter 2

# Preferences Heterogeneity and adherence to guidelines for the management of type 2 diabetes (T2DM): findings from the experimental module in the English Longitudinal Study of Ageing (ELSA)

## 2.1 Introduction

Non-adherent behaviour to the guidelines for managing T2DM can lead to uncontrolled diabetes [15]. Uncontrolled T2DM can result in severe complications [50, 51], unplanned hospital admission, and increased healthcare utilisation and costs [52]. For example, people living with T2DM are more than twice as likely to experience cardiovascular complications (Angina, Myocardial Infarction, Heart Failure and Stroke) and almost four times more likely to require renal replacement therapy than the general population [50]. The prevalence of T2DM is 6 per cent of the total population in England and Wales. Data from Hospital Episodes Statistics (HES), show that it accounts for 25 to 30 per cent of all the admissions for cardiovascular diseases and 40 per cent of hospital admissions for lower limb amputations [50]. However, as is know, if T2DM is well controlled, the risk of experiencing these complications can be significantly reduced [31, 53].

The National Institute for Health and Care Excellence (NICE) in 2015 introduced a personalised care planning approach to help people living with T2DM manage their condition better [14]. This approach suggests nine key T2DM processes that all people with T2DM should adhere to, at least annually, see Table 2.1 [54]. Each annual care process was designed to help people with T2DM reduce the risk of experiencing long-term complications and, in turn, improve their overall quality of life [55, 56]. For example, tight HbA1c and blood pressure control can decrease the risk of microvascular complications. Results from the United

Kingdom Prospective Diabetes Study (UKPDS) showed that a decrease of 1 per cent in HbA1c reduces the risk of microvascular complications by 33% (p-value <0.0001) [57]. Diabetic nephropathy is also more common in people who suffer from hypertension and, thus, the rationale for regularly monitoring blood pressure among people with T2DM.

| **NICE, recommended care processes** | **Benefit** |
|---|---|
| 1) Cholesterol measurement | Managing CVD risk |
| 2) Serum creatinine measurement | Managing the risk of kidney disease |
| 3) Smoking status | Managing CVD risk |
| 4) BMI | Managing risk of T2DM complications |
| 5) Foot Examination | Managing the risk of foot ulcer |
| 6) Blood Pressure measurement | Managing CVD risk |
| 7) HbA1c measurement | Managing risk of T2DM complications |
| 8) Urine albumin measurement | Managing the risk of kidney disease |
| 9) Eye screening | Managing the risk of developing retinopathy |

**Table 2-1: Care processes for managing T2DM.**

Blood pressure and serum cholesterol, Body Mass Index (BMI), and smoking history checks are essential parameters to be monitored to manage cardiovascular risks in people living with T2DM [50, 55]. Elevated BMI above 30 $kg/m^2$, smoking and high level of serum cholesterol in the bloodstream may damage artery walls, which can become blocked and increase the risk of cardiovascular complications (coronary heart disease, angina, myocardial infarction, heart failure and stroke). Blood vessels provide the nerves with the necessary nutrients for optimal functioning [58]. Suppose this mechanism does not function correctly; in that case, there may be permanent damage to the nerves, known as diabetic neuropathy, and eventually, lead to foot ulcers and, in extreme cases, lower limb amputation (toes, feet and legs). Diabetes is the leading cause of amputation in the UK. As such, a specific check that involves regular surveillance of the status of patients' feet has been designed to prevent

this severe complication [50]. Two checks should be performed annually to manage kidney complications. One is the serum creatinine test, which measures the level of creatinine (a chemical waste product produced by muscle metabolism) in the bloodstream to assess liver function [58]. The other is the urine/ albumin creatinine ratio (ACR) check; a test performed to verify the presence of protein in the urine as a possible marker for underlying kidney malfunctioning. Finally, the Digital Retinal Screening is a photographic eye test to establish potential retinopathy (eye disease).

The most recent National Diabetes Audit report [17] shows that the achievement of these processes has been delivered quite consistently overall, see table 2.2. If each process is considered independently, key indicators for T2DM such as HbA1C, blood pressure and cholesterol have an uptake that stands well above 90 per cent [54]. The uptake, however, results considerably lower if healthcare processes are considered simultaneously [17]. As a result, less than one in two people adhere to all the nine health processes recommended by the guidelines. T2DM management is complex and requires all the recommended care processes to be achieved by individuals to reach potential health gains entirely [55].

| **NICE care process** | **England 2015-2016 (per cent)** | **England 2016-2017 (per cent)** |
|---|---|---|
| 1)Serum cholesterol | 93.01 | 93.1 |
| 2) Serum creatinine | 94.08 | 95.1 |
| 3) Smoking history | 85.04 | 85.7 |
| 4) BMI | 82.04 | 83.3 |
| 5) Foot risk surveillance | 87.1 | 79.4 |
| 6) Blood pressure | 95.08 | 90.06 |
| 7) HbA1c | 95.01 | 95.03 |
| 8) Urine albumin/creatine ratio | 66.08 | 65.03 |
| Eight care processes | 53.9 | 47.7 |
| Retinal screening | n/a | n/a |

**Table 2-2: Percentage of people with type 2 and other diabetes receiving NICE recommended care processes by audit year in England, 2015-16 to 2016-2017.**

Therefore, while regular monitoring of key biomarkers is at the centre of T2DM guidelines [14], adherence to the recommended medical tests suggested by the NICE [54] remains low. This is likely to lead towards problems because people with T2DM who regularly attend outpatient appointments have better health outcomes compared to people who regularly miss appointments as a recent systematic review demonstrates [59]. Similarly, another study found that people who attended medical checks over the past year i.e., lipid test, eye exam, urine analysis and HbA1c test suggested by the American Diabetes Association (ADA) guidelines had better health outcomes compared to the people who did not attend the same checks [31]. In consideration of a record number of more than 4.3 million people already diagnosed with T2DM in the UK plus a further 850,000 undiagnosed [60] efforts should be made to better understand the key drivers that may increase adherence to the annual medical health checks for T2DM management and improve the health outcomes of the people living with T2DM. This is especially true for those risk factors beyond the well-established “classic socio-demographic” information such as age, gender and ethnicity [54]. Given the importance of adherence to T2DM medical checks, this aspect requires further investigation.

### 2.1.1 Theoretical framework

As it will be throughout the entire thesis, the framework of reference for this analysis is the Grossman model of the demand for health [61, 62]. The central aspect of this framework is that health is demanded for both utility and investment reasons, e.g., health is both a consumption good and an investment good. Therefore, the demand for health consists of a consumption effect, which yields

direct utility and an investment effect that will ultimately increase the number of days available to the consumer for market and non-market activities.

According to this framework, a person inherits an initial stock of health that depreciates with age and increases with investments in health, e.g., following a healthy diet, engaging in physical activity, or taking medications. Always, in this framework, economics agents' final aim is to optimise the level of their investment in health to maximise their lifetime utility. Individuals with a strong preference for present consumption over future consumption e.g., high discount rates, may not be willing sacrifice current utility for a greater reward more distant into the future and decide not to adhere to the guidelines for T2DM management. Conversely, individuals characterised by low discount rates may do the opposite and be more willing to sacrifice immediate utility to benefit for a greater reward in the long run and, therefore, be more likely to adhere to the guidelines for T2DM management. Since health behaviour depends on individuals' choices, time preferences may play a significant role in the final individuals' decision to input the optimal level of investment in their health. Grossman did not explicitly evaluate the consequences of different time preferences rates on health behaviour. However, as explored in the empirical literature on the topic, individuals' decision to engage in healthy behaviour requires a short-term 'losses' of utility to benefit from an even greater utility in the long run [40]. A commonly known example is an individual's decision to go to the gym or not [63]. Undoubtedly, this activity entails a short-term effort (and thus an immediate loss of utility) compared to more immediately pleasurable activities such as enjoying a tasty meal. However, it is equally valid that the well-formed habit of going to the gym regularly will bring greater utility in the long run.

Furthermore, as already mentioned in the introduction of this chapter, individuals who adhered to the medical checks recommended by the guidelines for T2DM

experienced fewer T2DM related complications than individuals who did not adhere to the same medical checks. Considering this trade-off between short-term cost and long-term benefit, it can be assumed that all else being equal (age, income, education), individuals with high time preferences rates will invest less in their health than their low time preferences rates counterparts [21, 24, 40, 64]. The same trade-off also exists from the opposite perspective, i.e., forgone presents utility to avoid longer-term harms such as developing T2DM complications [27].

There is also no explicit mention of risk preferences in the Human-Capital model's original formulation. One of the main assumptions of Grossman's model was that of perfect knowledge and perfect information, which made risk preferences irrelevant. If individuals, when facing choices, are perfectly aware of all the possible options and outcomes attached to their choices, they would be able to make an optimal allocation of their investment in health. In such a scenario, preferences would not affect how individuals allocate their time and effort to maximise their lifetime utility. Yet, uncertainty about future events was only introduced in a subsequent extension of the model by Wagstaff and his collaborators [65]. Similarly, as to what has been hypothesised for time preferences, risk preferences may also affect the individual's levels of investment in health. It can be assumed that risk-averse individuals are less likely to engage in health behaviour that can potentially bear risk in the long run [22, 27, 39, 40]. Therefore, a risk-averse individual will have a higher propensity to invest in their health e.g., more likely to adhere to the medical checks for T2DM than their more risk-tolerant counterpart [18, 19].

It is worth mentioning that other models, such as the Becker and Murphy model of "Rational Addiction" could have been equally chosen in place of the

Grossmann framework [66]. However, considering that the Becker and Murphy model seems particularly appropriate for the study of addictive behaviour, the Grossman model appeared to be a more suitable choice for what it pertains to the specific context of this thesis.

### 2.1.2 Objectives

By drawing on the seminal Grossman model of the demand for health as an underlying theoretical framework, this analysis examines whether and to what extent individual heterogeneity in time and risk preferences influences adherence to the medical checks suggested by the NICE guidelines for managing T2DM. Individuals' decision to adhere to the medical check for managing T2DM has consequences for multiple time periods. It requires decision-makers to trade-off costs and benefits at different points in time. For example, with medical screening, individuals incur immediate costs such as the time and effort required to undergo the examination to gain better outcomes in the long run, e.g., a lower probability of incurring T2DM-related complications. Time preferences are crucial in determining how individual's trade-off outcomes over time. Therefore, it can be assumed that the likelihood of complying with medical checks for T2DM may depend upon an individual's level of intertemporal preferences. This research hypothesises that all else being equal, individuals with high discount rates (more present-oriented) will invest less in their health, e.g., attending medical checks, compared to individuals with lower discount rates (more future-oriented).

A related but different concept to time preferences is represented by risk preferences [30]. While the former relates to individual decision-making over time, the latter focuses on individuals' decision-making under risk. These two are distinct concepts, but as the evidence suggest they are intertwined. As noted by Andreoni and Spenger: "The present is known while the future is inherently risky".

This is problematic when studying time preferences since uncontrolled risk can generate apparently present-biased behaviour"[30]. The authors conducted an intertemporal allocation experiment at the University of California San Diego in April 2009, where 80 college students were asked to choose between smaller sooner rewards and greater later rewards. They repeated the experiment under varying risk conditions and found that this manipulation in the risk parameter affected the participant's intertemporal decision-making. Therefore, uncertainty is another crucial aspect that influence intertemporal decisions. Future health outcomes are uncertain since there is no certainty about the incidence of illness. For example, complying with the medical check for T2DM management does not guarantee that the individual will not experience complications. Thus, individuals' attitudes towards risk may play a role in adhering to the medical check for T2DM. In summary, risk preferences represent the extent to which individuals are willing to accept or avoid uncertainty. For instance, risk-averse individuals may be more concerned about the potential risk associated with uncontrolled T2DM and, therefore, be more prone to adhere to the medical checks for T2DM management than their more risk-tolerant counterparts. It is worth noting here that the relationship between preventative health behaviour might become more ambiguous if also uncertainty about the treatment is considered. If there is only uncertainty about the incidence of illness but not about treatment, as seen above, higher risk aversion should increase preventive health behaviour and, consequently individuals' health. However, if there is also uncertainty related to the efficacy of the treatment, the relationship between risk preference and preventative health behaviour might become more ambiguous. For example, if early detection of a condition or an illness leads to costly treatment that may or may not be effective, greater risk aversion may decrease the probability of

engaging in preventative health behaviour. This is the case of a study by Picone et al., 2004 [18], which, as seen in more detail in the section about the literature review, found that risk averse individuals are less likely to engage in medical screening for breast cancer.

The current research will test two hypotheses regarding this potential association between time and risk preferences and the medical check suggested by the guidelines for T2DM management:

1. Individuals with low discount rates, i.e., more future-oriented, are more likely to adhere to the annual medical checks for T2DM management than their high discount rate counterparts. Conversely, individuals with high discount rates i.e., more present-oriented, are less likely to adhere to the annual medical checks for T2DM management than their low discount rates counterparts.
2. Risk-averse individuals are more likely to adhere to the medical checks for T2DM management compared to their more risk-tolerant i.e., risk-lovers and risk neutral counterparts. Risk-neutral individuals are more likely to invest in their health compared to their risk tolerant equivalent.

In summary, the present analysis will tackle the gap in the existing literature by exploring whether and to what extent heterogeneity in risk and time preferences may contribute to explaining adherence to the medical checks for T2DM using a sample of community-dwelling older adults and preferences elicited through a laboratory experiment.

### 2.1.3 Literature review

Several studies from the economics and psychology literature, link the attitude towards risk and the ability to wait for deferred gratification, i.e., time and risk

preferences to health behaviour, including adherence to medical checks [18, 19, 21-27, 39-41, 67]. Table 2.3 summarises studies that evaluated the relationship between time preferences and a wide range of health-related behaviours, including adherence. Studies were retrieved by searching Google Scholar using free text words such as ‘time preference’, ‘risk preference’, ‘health behaviour’, ‘medical check’, ‘type 2 diabetes’ and all their possible combinations. Subsequently, I hand-searched the list of the selected references for further studies which could be relevant to the objectives stated in section 2.1.2. The main features of the studies included in the final literature review are summarised in Table 2.3. What is more, they are reported in temporal order, with studies that specifically evaluated behaviour related to T2DM positioned at the top of the table. For ease of interpretation, each study has been assigned a specific colour (last column of the table). Studies ‘highlighted’ in green show results in line with the *a priori* hypothesis that individuals characterised by a low discount rate (e.g., willing to wait for a greater reward more distant into the future) are more prone to invest in their health compared than their high discount rate counterparts. In addition, these studies also displayed a statistically significant coefficient for the time preference variable. Studies are ‘highlighted’ in yellow when the coefficient for the time preference variable did not reach statistical significance. Finally, results are highlighted in red when the coefficient for time preference reached statistical significance, but the sign is not in line with the expectation.

**Table 2-3 summary of the studies included in the literature review for time preference.**

| Study | Was the study specifically focused on T2DM? (Yes /no) | Time preference measure employed by the study | Type of behaviour assessed by the study | Findings | Colour |
|---|---|---|---|---|---|
| Madsen et al., 2019[28] | Yes | Systematic review which included 12 articles. Time preferences were elicited both through survey questions and choice tasks. | Use of T2DM recommended care, self-assessed control of diabetes, general health and HbA1c. | They found associations between measures of time preferences, diabetes self-management behaviour and clinical outcomes. | Green |
| Karl et al., 2018[25] | Yes | Time preferences were measured by 4-point Likert scale obtained from one question included in the survey KORA (Cooperative Health Research in the Region of Augsburg) | T2DM self-management behaviour score which involved self-care activities such as wound checking, blood pressure and blood sugar measurement. | High time preference rates (more present oriented) were associated with a significantly lower sum of self-management behaviour (β=-0.29, 95% CI [-0.54, -0.04]). The interaction model showed that low time preference rates (more future oriented) were only associated with better self-management when combined with a high outcome expectancy (β=0.05, 95% CI [-0.28, 0.39] vs β=0.27, 95% CI [-0.09, 0.63]). | Green |
| Mørkbak et al., 2016[26] | Yes | Time preferences elicited through a discrete choice experiment (DCE) involving two lottery games involving different potential payoffs. Participants could enter at no cost. | Self-care behaviour – physical exercise, obesity, T2DM literacy, and health outcomes – glycaemic control | Present biased individuals are less likely to engage in self-care behaviour and thus more prone to the onset of T2DM at an early age and have a poorer prognosis after diagnosis. The authors concluded that this effect is causal. | Green |
| Van der Pol et al., 2016[40] | Partly since the sample comprised patient with chronic health conditions, | Time preferences were measured using a question about financial planning horizon as a proxy. The question was asked as a part | Adherence to physician advice on health behaviour change (advice to change dietary and | Individuals with low time preferences rates (more future oriented) are more likely to adhere to advice on physical activity. The marginal effects show that at the mean value a unit increase in | Green |

| | | | | | |
|---|---|---|---|---|---|
| | including T2DM. Other conditions were, hypertension, heart disease and stroke | of larger cross-sectional survey of chronic disease patients in Western Canada, the Barriers to Care for People with Chronic Health Conditions (BCPCHC) survey. In the survey question used to measure time preference respondents were asked "*In planning your savings and spending which of the following time periods is most important to you*?". The available answers included 6 options with time periods ranging from 1 week to more than 10 years. | physical activity behaviour). | planning horizon is associated with a 1.9 % increase in the probability of adhering to advice on physical activity. In the case of adherence to advice on eating certain foods, planning horizon is statistically significant for males but not for female. | |
| Sloan et, al.,2009[27] | Yes | Binary indicator (yes or no) retrieved from a statement included in the HRS which asks respondents how much they think about the future on a scale from 1 to 5. | An index reflecting individual's use of recommended care and practices during the last year (hA1c, cholesterol, eye examination, BMI, regular exercise, compliance with T2DM medication) | Time preference was not statistically significant in any of the model. | Yellow |
| Jingrong Zhu et al., 2020[41] | No | Multiple price list experiment | Aspirin therapy for cardiovascular prevention | Patients with high-time preference rates (more present oriented) were less likely to begin with the use of aspirin | Green |
| Bayer et al, 2019[68] | No | Six item questionnaire which asked participants to choose between receiving a certain sum of money today or receiving a sum of money in | Economic conduct i.e., how clinical depression (and its severity) affects economic conduct | Individuals with depression are more likely to prefer current consumption over future consumption. | Green |

| | | | | | |
|---|---|---|---|---|---|
| | | the future. Rewards were delayed by a minimum of month to a maximum of 5 years. Based on the responses to the questionnaire they calculated a discount rate based on an exponential model. | (measured by a 6-item administered questionnaire). | | |
| Mole et al., 2015 [69] | No | A 27-item self-administered questionnaire in which participants had to choose between a small immediate reward and a larger delayed reward. Discounting curve was calculated used the formulae as in Petry, N (see paper below). | Binge eating disorder (BED), abstinence to alcohol dependence. | All three intervention groups (obese participants with BED, obese participant without BED, and abstinent alcohol dependent) had greater delayed discounting compared to healthy volunteers. | Green |
| Eberth et al., 2020[24] | No | Preferences were elicited through two hypotheticals questions to elicit time preference for monetary outcomes included in the National Longitudinal Survey of Youth 1972 (NLSY79). These two questions asked the participants to choose between monetary trade-off between now and 1 year delay; and now vs 1 month. A quasi-hyperbolic model was assumed. | Transition in physical activity behaviour (from inactive to active and vice versa) over time Three types of physical activity behaviour were included in the analysis: strengthening exercise activity, low/moderate physical activity, and vigorous physical activity. | Present bias impact maintenance but not initiation of physical activity behaviour. The time preference rate impacts maintenance of strengthening exercise in men only. | Green (maintenance of physical activity) yellow (initiation of physical activity) |

| | | | | | |
|---|---|---|---|---|---|
| Shuval et al., 2017[23] | No | Time preferences elicited based on hypothetical choices (a dollar amount today or a more considerable amount in 30 days and a dollar today versus an even greater amount in 60 days) | Physical activity | Individuals with low time preference rates (more future oriented) were 1.2 times more likely to meet guidelines for physical activity than those that were not future oriented (30 days: OR=1.24, 95%CI 1.02-1.52; 60 days: OR= 1.23, 95%CI=1.06-1.44) | Green |
| Dean et al., 2011 [70] | No | Delay discounting test (DDT (Kirby et al. 1999) in which participants had to choose between two hypothetical options across 27 trials. | Smoking | Smokers discounted delayed rewards to a greater extent than nonsmokers (log total k value, t(61)=−2.90, p=.012) | Green |
| Bradford, 2010[21] | No | Latent time –preferences rates were elicited through a series of time preference question included in the HRS where respondents had to choose between hypothetical pay-offs available at different time-points. | Rates of recent mammograms, breast exams, Pap smears, prostate exams, cholesterol testing, flu shots, and dental visits, and non-smoking status | High discount rates status is found to have a negative marginal association on the probability that respondents had recent mammogram use (–15.1%; P=0.001), Pap smear use (–8.3%; P=0.049), prostate examination use (–20.4%; P=0.003), dental visits (–24.8%; P=0.001), cholesterol testing (–12.4%; P=0.001), flu shot usage (–11.1%; P=0.005), rates of vigorous exercise (–15.1%; P=0.001), non-smoking status (–10.4%; P=0.001), and undertook all measured health habits (–7%; P=0.001) | |
| Picone et al., 2004[18] | No | Time preferences were measured using a proxy for financial planning horizon based on a question included in the first wave of the HRS. Possible answer included periods for financial planning horizon ranging from less than a year up to 10 years or more. | Probability to attend each of the following examination: regular breast self-exams, mammograms test, and Pap smears test, three tests together. | Women with high time preferences rates are less likely to engage in breast self-exam, mammography, and undergo all three tests together. | Green |

| | | | | | |
|---|---|---|---|---|---|
| Petry Nancy, 2000 [71] | No | Choice list between smaller immediate rewards and larger delayed rewards of different magnitudes ($1000 and $100) and different types (money and alcohol). A titration procedure was employed to determine indifference points that allowed to calculate indifference points at various delays. The current value of a delayed rewards was calculated using the formulae: V=A/(1+kD). Where A is the non-discounted reward, D is the delay duration and K is an empirically derived constant proportional to the degree of delay discounting. Magnitudes of immediate rewards and intervals were presented in both ascending and descending order. | Alcohol (comparison of delayed discounting of money and alcohol between actively alcoholics, abstinent alcoholics, and controls). | Current alcoholics discounted delayed reward more rapidly than both abstinent alcoholics and controls (without a history of alcohol or other drug abuse) in three of the four comparisons made using contrast procedures. Smaller reward tended to be discounted more rapidly than larger ones. Alcohol was discounted more rapidly than money. | Green |
| Kirby & Bickel, 1999[67] | No | Monetary rewards available immediately ($11 - $80) and larger rewards ($25 - $85) available after delays ranging from 1 week to six months. | Drug addiction (heroin) | On average, heroin addicts discount rate was twice those of control (p = .004). Furthermore, discount rate was positively correlated with impulsivity as measured by self-report questionnaire. | Green |
| Bickell et al., 1999 [72] | No | List of choice task where participants had to indicate their preference between | Smoking (comparison of delayed discounting for | Smokers discounted monetary rewards more steeply than did never smoker or ex-smokers. Non-smokers and ex- | Green |

| | | | | | |
|---|---|---|---|---|---|
| | | immediate vs delayed rewards expressed in monetary terms. The same procedure was repeated with cigarettes but for smoker only. A titration procedure was employed to determine the indifference points at various delays. The discounting was calculated by applying the hyperbolic equation as in Petry, N 2000 (please see above). They An exponential discounting equation was also tested. The monetary reward ranges from $1 to $ 1000. Delays ranged from 1 week to 25 years. | money and cigarette between smoker, ex-smoker and never smokers) | smoker did not differ in their discounting of delayed outcomes. Smokers discount cigarettes to a greater extent than money. The hyperbolic discounting equation fitted the data better than the exponential one. | |

In a seminal paper about intertemporal choices, Frederick and co-authors pointed out how the traditional discount utility model (DU model), originally proposed by Samuelson in 1937 and widely used by economists has several limitations which limits its descriptive validity, what they define as a "growing list of DU anomalies"[29]. They also distinguish time preference from time discounting which according to the authors own word can be described as follow "We use the term time discounting broadly to encompass any reason for caring less about a future consequence, including factors that diminish the expected utility generated by a future consequence, such as uncertainty or changing tastes. We use the term time preference to refer, more specifically, to the preference for immediate utility over delayed utility". Moreover, they also examined whether time preferences itself may consist of distinct psychological trait that may have important implication for intertemporal choice and that can be separately analysed. One of these trait is impulsiveness which can also be found in the psychology literature, for instance in the Kirby's *Delayed discounting* model[67]. According to this theory, the present value of a reward diminishes as the delay to that reward increases. Therefore, the more distant into the future a reward is the lower its present value as well as its chances to be chosen against others current alternatives. The rate at which the present value of a reward diminishes as the delay to that reward increases is represented by the *discount rate* to distinguish between intertemporal effects arising due to time preference versus those due to changes in utility as a function of time. Research from Kirby and Bickel [67] tested the Delayed discounting model empirically. The authors elicited delay-discounting rate both among an intervention group of 56 opioid-dependent participants enrolled in the Substance Abuse Treatment Clinic at the University of Vermont and 60 randomly selected participants from the general population.

All the participants enrolled in the study were presented a lottery game involving 27 choices between smaller monetary ($11 – $80) rewards available immediately and larger delayed rewards ($25 – $85) available after delays ranging from 1 week to 6 months. Participants' discount rates were estimated from these set of choices and on average those of heroin addicts were double the rate of those from the control group ($p = 0.004$).

As reported in table 2.3, several studies support the theory that time preferences may be associated with health behaviour, including medical check-ups. For instance, an empirical investigation [18] with data from the US-based survey Health and Retirement Study (HRS), found that women with a short time horizon had lower predicted probability ($\beta = - 0.135$, p-value <0.001) to demand cancer screenings (mammography, pap-test, and self-examination). These results hold even after adjusting for expected longevity. Expected longevity is particularly important in this context since it measures the initial health stock. Therefore, it is likely to influence the demand for medical screenings, i.e., higher life expectancy implies higher payoffs of health investments. Time preferences are also associated with cholesterol testing (–12.4%; P=0.001), flu shot usage (–11.1%; P=0.005), rates of vigorous exercise (–15.1%; P=0.001), non-smoking status (–10.4%; P=0.001) [21]. Two recent studies that linked time preferences to adherence to T2DM management behaviour are essential for this thesis [25, 26]. Research using survey data from the German KORA suggests that a higher discount rate was associated with a lower ($\beta$=-0.29, 95% CI [-0.54, -0.04]) T2DM self-management behaviour score which involved self-care activities such as wound checking, blood pressure and blood sugar measurement. A study from Denmark linking patient registry and survey data found that people with inconsistent time preferences had significantly worse self-care behaviour –

physical exercise, obesity, T2DM literacy, and health outcomes – glycaemic control and quality of life. The author also conclude that these effects are causal.

As briefly describe above, I also report an additional table, which summarises the empirical studies that evaluated the relationship between risk preference and adherence to a wide range of health-related behaviour, including medical check for T2DM table 2.4. Following a similar approach to what has been described above for time preference, the studies included in the literature review were retrieved by searching Google Scholar with search terms such as “risk-preferences”, “attitude towards risk” “health behaviour”, “T2DM” and all the possible combinations between these words. This table follows the same structure of table 2.3 above, e.g., the empirical investigations are presented in temporal order starting from studies which were specifically focused on type 2 diabetes.

## Table 2-4 Summary of the studies included in the literature review for risk preferences.

| Study | Was the study specifically focused on T2DM? (Yes or no) | Risk preference measure employed by the study | Type of Behaviour assessed by the study | Findings | Colour |
|---|---|---|---|---|---|
| Simon-Tuval et al., 2017[19] | Yes | Lottery choice tasks in which participants made ten hypothetical decisions between different monetary payoffs attached to them. | Adherence of patients with type 2 diabetes mellitus to medications | Compared to others risk-seeking patients are less adherent to oral hypoglycemic agents OHA therapy Specifically, these patients were 19.5 percentage points less likely to have an average proportion of days covered PDC of > 80% (p <.05) | Green |
| Sloan et, al.,2009 [27] | Yes | Survey question on risk preferences in the financial domain from the HRS. Possible answers were categorized on four-point scale varying from low level of risk tolerance (very risk averse) to risk neutral. | An index reflecting individual's use of recommended care and practices during the last year (hA1c, cholesterol, eye examination, BMI, regular exercise, compliance with T2DM medication) | Risk preference only significant for HbA1c testing and only for the low-med risk tolerance category, which had 1.81 the odds of complying with HbA1c, testing 95% Cis (1.03–3.18). | Yellow |
| Van der Pol et al., 2016[40] | Partly since the sample comprised patient with chronic health conditions, including T2DM. Other conditions were, hypertension, heart disease and stroke | Survey questions from BCPCHC which asked respondents about their willingness to take risks on a ten-point scale (from 1 "unwilling to take risks" to 10 "fully prepared to take risks"). | Adherence to physician advice on health behaviour change (dietary and physical activity changes). | Marginal effects from probit regressions show no statistically significant association between risk preferences and adherence (both diet and physical activity advice). | Yellow |
| Jingrong Zhu et al., 2020[41] | No | Multiple price list experiment | Aspirin therapy for cardiovascular prevention | Risk-seeking behaviour were significantly associated with both nonparticipation (P < .01) and lower compliance (P < .05). | Green |
| Y. a. M. Bayer, et al., 2019. [68] | No | A 36-points index based on a questionnaire consisting of six statements regarding risk taking behaviour | Economic conduct i.e., how clinical depression (and its severity) affects economic conduct (measured by a 6-item administered questionnaire). | Individuals suffering from depression tend to take more economic risks compared to healthy subjects. | Green |
| Galizzi and Miraldo, 2017 [39] | No | Incentivized Laboratory experiment (multiple price list design) involving a total of 120 young adults. Participants were presented a series of binary lotteries. Based on the responses | BMI, Healthy Eating Index (an overall indicator of nutritional quality) and healthy risky behaviour (smoking, alcohol) considered together. | Healthier nutritional habit is associated with higher risk aversion in male only but not in females. Similarly, males with high BMI appear more risk seeking. Male smoking status is not associated with risk preferences. | Green (healthy eating) yellow (smoking alcohol) |

| | | | | | |
|---|---|---|---|---|---|
| | | to these tasks the authors constructed a CRRA. | | | |
| Pfeifer 2012[22] | No | Survey question from The German Socio-Economic Panel (GSOEP) which asks respondents their willingness to take risks with respect to health issues and in general. Possible answers are categorized on a 10 points Liker scale. | Smoking | Individuals, who are more health risk taking, are more likely to be smokers and have a higher demand for cigarettes smoked per day (Individuals who are 0.1 point more health risk taking, are on average 2.6 percentage points more likely to smoke). | Green |
| Dean et al., 2011 [70] | No | Balloon analogue risk task (BART) a computerised task of risky decision making designed to assess risk preferences. Participants must inflate computerised balloons. Th goal is to inflate the balloon to is maximum but no more. Each "successful" pump worth 2 $ cents but is the balloon is inflated too much past its explosion point, no money is earned from that trail by the participant. | Smoking | Smoker did not display greater risk taking on the BART scale compared to non -smokers. They also found that the two-group had differential adaption in risky behaviour with non-smokers exhibiting more pumping. | N/a |
| Picone et al., 2004[18] | No | Three questions from the HRs which asked respondents to choose from hypothetical gambles with different payoffs attached to them a different probability to be realized | Probability to attend each of the following examination: regular breast self-exams, mammograms test, and Pap smears test, three tests together | Less risk averse individuals tend to be more likely to undergo testing (all three tests). No significance for other outcomes but the sign was as expected e.g., positive. | Green |

Relatively fewer studies investigated the effect of risk-preferences on health behaviour compared to the literature available on time preferences. However, albeit to a slightly lesser extent than time preferences, they also support the hypothesis that risk adverse individual are more prone to engage in health protective behaviour. Arguably, findings from the present literature review, appear consistent with the theory that time, and risk preferences influence a wide range of health behaviour, including medical check-ups, and therefore may be an important component to consider in advancing the discussion on how to improve adherence to NICE T2DM management guidance.

The contribution of this research is twofold. First, this study investigates whether time and risk preferences influence adherence to T2DM management behaviour. Previous research focused on time preferences as a potential predictor of adherence to T2DM management behaviour[28].

However, to the best of my knowledge, fewer studies also included risk preferences in its model, a potential confounder that might influence the relationship between preferences and adherence to T2DM management. Secondly, this is the first study in the UK to evaluate the effect of time and risk preference on adherence to medical checks for T2DM management by using preferences elicited through a laboratory experiment instead of relying on self-reported proxies. Although proxies for preferences such as financial planning horizon have been shown to perform well, using measures elicited through an incentivised laboratory experiment could bring valuable insight into the determinants of adherence to T2DM medical checks. Advancing the discussion on the possible determinant of adherence to T2DM management is a salient aspect given the potentially devastating complications that may arise from T2DM. Furthermore, underpinning the mechanism behind non-adherence is particularly

important among older people, where the prevalence of T2DM is much higher than in the general population[73].

## 2.2 Methods

### 2.2.1 Data

Data were obtained from The English Longitudinal Study of Ageing (ELSA). The ELSA is a longitudinal panel survey of people living in England aged 50 or more. It is a multidisciplinary study which collects information on people's socio-demographic characteristics, physical and mental health, health behaviour and finances. [34]. The sample was initially drawn from households that previously responded to the Health Survey for England (HSE) for the years 1998, 1999 and 2001. The study began in 2002, and the same respondents are interviewed every two years. Data are collected using computer-assisted personal interviews and self-completion questionnaires. Furthermore, an additional nurse visit occurred every four years where information on participants' biomarkers was also collected. More than 18,000 unique individuals have taken part in the study since it started in 2002 (Wave 1), and the latest available wave at the time of this research was collected in 2016 (Wave 8). The present study uses data on socio-demographic characteristics, income, and health behaviour from the ELSA interviews conducted during the Wave 4, Wave 5 and 6 as will be explained in section 2.2.2 below. This section will provide more details on how the samples for the analysis have been constructed. In total, 11,050 respondents participated in the ELSA Wave 4, 10,274 in Wave 5 and 10,601 in Wave 6.

Furthermore, alongside the main questionnaire, an experimental module [42] was introduced during Wave 5 for the first and only time in the ELSA. A randomly selected sub-sample of 1501 ELSA participants aged 50-74 was asked to participate in a computer-assisted laboratory experiment to measure people's

attitudes towards risk and their willingness to postpone rewards when making financial decisions, i.e., time and risk preferences, although limited to financial decisions. The risk module was designed as a standard lottery-type laboratory experiment where respondents had to accomplish three different sets of choice tasks. The first element involved two groups of incentivised time-preferences tasks with tasks of six choices each. Each set was made of a multiple price list, in which subjects had to choose between a smaller pay-off of immediate availability and a larger delayed pay-off only available after either one or two months. The second element entailed a list of ten risk preference tasks where respondents had to choose among six different options involving different risk levels. Each set of tasks and their relative payoffs will be described in more detail later in sections 2.3.1.3 and 2.3.1.5, respectively.

The experiment was incentivised, meaning respondents received a real monetary payment at the completion of the module, depending on their responses to the tasks. Respondents were offered a sum of £10 at the beginning of the module to participate in the experiment, and subsequently, at the end of the module, the computer-assisted personal interviews (CAPI) programme randomly picked one of the 22 tasks. The respondent won the amount of money corresponding to their choice for this task. Therefore, respondents could win a maximum amount of £80 (£10 initial sum plus £70 from token F rectangle game 2 of the risk preference task as described in Figure 2.1), or they could lose, in the worst-case scenario, £5 of the initial sum (rectangle game 1 token F of the risk preference task of which a screenshot is available in the appendix A.1). Consequently, the minimum amount of money participants was entitled to win was £5, while the maximum amount was £80. The expected average payment amounted to £ 35. It is worth noting that the entire experimental module was incentivised since the monetary

pay-off from which the financial reward was calculated was randomly selected among the 22 games played by the respondents (12 for time preferences and 10 for risk preferences). Incentivised choice tasks in which individuals receive real monetary rewards dependent on the outcome of their responses are 'regarded as the gold standard for preference elicitation in experimental economics' [74] and present several advantages over self-assessed measures [42]. Firstly, the rationale behind the incentivization is that individual will reveal their true preferences only if their choices have real monetary consequences. This also means that incentivized choice task may provide different information compared to self-assessed measure i.e., self-reported time horizon and incentivised time choice tasks are in some contexts weekly related, as it is the case of the ELSA for time preferences [42]. Secondly, the fact that individuals make real choices with monetary consequences makes the incentivised choice task less subject to 'hypothetical bias'. However, they come with the limitation that incentivised laboratory experiment are costly to organise, effectively limiting the sample sizes and statistical power. Additionally, they contribute to higher administrative expenses [75]. Finally, preferences elicited in the monetary domain may differ from preferences in the health domain. However, a study by Fredslund et al. 2018 [76] found no difference between time preferences measured in the monetary and the health domain, apart from minor differences in specific subgroups.

### 2.2.2 Construction of the sample

Two different samples were used in the analysis. The former sample comprises all the ELSA participants who self-reported a diagnosis of T2DM; the latter sample includes all the ELSA participants who self-reported at least one of the following diagnoses: T2DM, high blood pressure or high cholesterol. The

procedure for constructing these two samples will be described in more detail in the following sections 2.2.2.1 and 2.2.2.2.

#### 2.2.2.1 Type 2 diabetes sample

As reported in the previous section, the risk and time preferences variables were only collected during wave 5. Despite the evidence on the stability of time and risk preference has yet to reach conclusive results [77], they have commonly been assumed by the standard economic theory to be innate characteristics which may be considered stable over time [78] . Therefore, to gain as much statistical power as possible given the available data, I merged individual-level risk and time preferences indicators contained in the wave 5 risk module to the wave 4 core dataset by performing a 1:1 matching on the common unique individual identifier contained in all the ELSA modules, only observation who matched were retained. I then repeated the same process but for the wave 6 instead, merging the risk and time preferences variables to the wave 6 core questionnaire, always with a 1:1 matching. Even in this case only observations who appeared in both datasets were taken. Finally, I appended these two newly created datasets to the wave 5. I only merged the wave 5 preferences variables to the two most adjacent waves (wave 4 and wave 6) because no additional participants took part in the wave 5 risk module (and contemporarily had T2DM) in waves 3 and 7, respectively. If an individual appeared more than in one wave, priority was given to the observation pertaining to wave 5, the wave in which the time and risk preferences variables were collected. This procedure aimed to identify participants who participated in the risk module but did not report their diagnosis during wave 5 but rather in one of its adjacent waves i.e., wave 4 and wave 6. Despite the effort this resulted only in meagre gains and only six additional participants were identified according to this procedure.

Subsequently, I was able to identify the diabetic population thanks to an indicator in the main questionnaire, which asks participants whether they have ever been diagnosed with T2DM or high blood-sugar reading by a doctor or a nurse, more specifically *"Have you ever been diagnosed with type 2 diabetes or high-blood sugar reading (yes/no)?"*. This entire process led to a final sample of 93 unique participants who both participated at the risk module in wave 5 and had self-reported a diagnosis of T2DM.

#### 2.2.2.2 Type 2 diabetes, high cholesterol, and high blood pressure sample

An additional sample was constructed to increase statistical power, including, in addition to people diagnosed with T2DM, also participants living with other chronic conditions, specifically high blood pressure (hypertension) and high cholesterol. These conditions were selected because they share similarities that are not necessarily present in other long-term chronic health problems [79]. Firstly, they are often influenced by common behavioural risk factors, such as an unhealthy diet, physical inactivity, and excessive alcohol consumption. Secondly, they require ongoing management that involves lifestyle changes. Thirdly, these conditions may have extended asymptomatic periods. Finally, they are amongst the most prevalent chronic conditions that affect the elderly population. As a result, they may appear in co-morbidity more frequently than other combinations of long-term health problems. Conversely, other chronic conditions such as asthma or arthritis, do not necessarily share all these aspects. Likewise, it was the case for T2DM, it was possible to identify individuals diagnosed with high blood pressure and high cholesterol via two questions included in the Elsa main questionnaire which asked participants "*Have you ever been diagnosed with high cholesterol (yes/no)?"* and *"Have you ever been diagnosed with high blood*

*pressure (yes/no)?"*. This second additional sample counts 551 unique participants.

### 2.2.3 Empirical specification

#### 2.2.3.1 Dependent variables

*Adherence to the Medical Checks for T2DM Management*. Adherence was measured using three items included in the ELSA main questionnaire, which asked the respondents whether, over the last year, they had their (1) HbA1c and (2) blood pressure tested and their (3) feet examined by a doctor or a nurse. More specifically, these questions were worded as follows: (1) *In the past year, has any doctor or nurse checked your blood pressure? (yes/no)* (2) *Have you had a blood sugar test (glycosylated haemoglobin or fructosamine) test performed in the past 12 months? (yes/no) (3) In the past year, has any doctor or nurse examined your bare feet? (yes/ no).* These variables were dichotomised, and based on the participants' responses to the items mentioned above three binary indicators were constructed that were equal to one if the participants adhered to the check and zero otherwise. A comparison between the checks recommended by the National guidelines and the proxies for adherence I could recover from the ELSA dataset is reported in Table 2.5. For the sample comprised of patients with at least one chronic condition, the dependent variable will be represented by the blood pressure check only. The reason behind selecting this dependent variable in particular is because individuals who have type 2 diabetes mellitus, hypertension, or high cholesterol are more susceptible to developing cardiovascular diseases [80]. All the models were estimated using binary logistic regressions and the statistical package STATA 18 SE.

| NICE GUIDELINES (NG28) | |
|---|---|
| Diabetes process | Proxy (ELSA) for each diabetes process and their frequencies (N = 93). |
| Annual check for Hba1c | Whether the respondent had the Hba1c test in the last 12 months? (Yes = 67/ no = 26) |
| Annual check for Blood pressure | Whether the respondent had a Blood Pressure test in the last 12 months? (Yes = 87, no = 6) |
| Annual check for foot surveillance | Whether the respondent had a feet examination in the last 12 months? (Yes = 69 / no = 24) |

**Table 2-5: A comparison of the NICE Diabetes processes and their corresponding proxies as found in the ELSA.**

### 2.2.3.2 Explanatory variables

All the explanatory variables included in the analysis were obtained from the wave 5 ELSA main questionnaire, as described in the following sections 2.3.1.3, 2.3.1.5 and 2.3.1.7.

### 2.2.3.3 Time preferences variable

Measurements for the time preferences variables were retrieved according to the participants' responses to the incentivised time-preference tasks (or equivalently games) from the experimental module that occurred during the wave 5. The incentivised time-preference tasks comprised twelve tasks divided into two sets of six games each. In the first six tasks, respondents were asked to choose between pay-offs available in two weeks versus one month. For the subsequent remaining six tasks, the choice was split between pay-offs available in two weeks compared to pay-offs available in two months. As a result, the maximum number of times subjects could delay their choices was six for each list. A complete list of the twelve tasks and their relative payoffs are reported in Table 2.6 below.

| Choice | In two weeks | In one month | In two months |
|---|---|---|---|
| 1 | 25 | 26 | |
| 2 | 25 | 28 | |
| 3 | 25 | 30 | |

| | | | |
|---|---|---|---|
| 4 | 25 | 32 | |
| 5 | 25 | 35 | |
| 6 | 25 | 38 | |
| 7 | 25 | | 26 |
| 8 | 25 | | 30 |
| 9 | 25 | | 35 |
| 10 | 25 | | 37 |
| 11 | 25 | | 40 |
| 12 | 25 | | 45 |

**Table 2-6 Time preference tasks payoffs (£)**

According to the number of times they chose the delayed payoffs and assuming a linear utility function that does not correct for any heterogeneity in the curvature of the marginal utility, participants' time preferences were classified into seven categories following the formulae i.e., discount utility (DU) model[1] :

$$r = ((ai/aj)\text{^}(1/2.43)) - 1$$

Where $r$ represents the weekly discount rate, $ai$ and aj $(i, j_{, 1.....12})$ represents the delayed and non-delayed payoffs, respectively, and 2.43 was calculated on the assumption that one month is 31/7 = 2.43 and 2 months = 61/7 = 8.71 weeks. Each category corresponded to a specific weekly discount rate band as reported in the risk modules' technical report and table 2.7. This table reads in the following way: suppose for the sake of the argument that a respondent never chose the delayed reward when considering two weeks *versus* one-month pay-offs, then their discount rate was estimated as being more than 18.8%. Whereas if a

[1] The formula and its underlying assumption were retrieved by corresponding directly with the principal investigator of the ELSA risk module since this information was not available in the technical report.

respondent who always chose the delayed result when comparing two weeks against two months had a discount rate of 0.6%.

**Table 2-7 - Time preference task: implied weekly discount rate (ELSA)**

| Number of times choosing delay | The first list (2 weeks or one month) | The second list (2 weeks or two months) |
|---|---|---|
| 0 | >18.8% | >9.1% |
| 1 | 14.9 – 18.8% | 7.3 – 9.1% |
| 2 | 10.7 – 14.9% | 6.0 – 7.3% |
| 3 | 7.8 – 10.7% | 5.1 – 6.0% |
| 4 | 4.8 – 7.8% | 2.8 – 5.1% |
| 5 | 1.6 – 4.8% | 0.6 – 2.8% |
| 6 | <1.6% | 0.6% |

Therefore, the ELSA time and risk module contains two variables that describe the participants' time preferences. The first variable, called *shorter time trade-offs*, assigns respondents to a weekly discount rate based on tasks one to six. A second variable, *longer time trade-offs*, still give the respondent a weekly discount rate, but on tasks seven to twelve instead. Hence, these two variables describe essentially the same concept. The only difference is that the variable *longer time trade-offs* involve more delayed payoffs than *shorter trade-offs*, e.g., six weeks instead of two weeks (assuming 4 weeks in month), as shown in Table 2.6. Because T2DM is a lifelong condition and complications usually require time to develop, a longer trade-off time frame is considered a slightly more appropriate measure for time preferences as it pertains to our specific context and therefore will be chosen as the main measure for time preferences in the present analysis. However, it needs to be acknowledged that the 'long term' set of questions extends the period by only four weeks, likely representing a relatively minor difference considering that T2DM related complications take, on average, several years to develop. Therefore, the long-term definition used in is research is further from the usual long-term characterisation usually defined when discussing about

T2DM related complications. Subsequently, each of the two variables describing the participants' time-preferences was dichotomised into two different categories. All the participants who chose the delayed options 5 times or more were assigned to the category of *low-discount rate*, conversely all the participants who chose the delayed option 4 times or less were assigned to the category of *high discount rate*. The rationale behind categorising the time preference variables in this manner stemmed from the observation that longer and shorter trade-offs had a bimodal distribution with two distinct peaks or modes, as shown in Table 2.8. Consequently, the dataset displayed two prominent clusters or groups, one with low time preference rates and another with high time preference rates.

**Table 2-8 Frequencies distribution of the longer and shorter time trade-offs variables. The total number of delayed pay-off chosen by the participants in parenthesis.**

| **Shorter time trade-off** | Freq. | Percent |
|---|---|---|
| d> 0.1880 (0) | 19 | 20.43 |
| 0.1485 < d < 0.1880 (1) | 3 | 3.23 |
| 0.1069 < d <0.1485 (2) | 2 | 2.15 |
| 0.0779 < d <0.1069 (3) | 4 | 4.30 |
| 0.0477 < d < 0.0779 (4) | 10 | 10.75 |
| 0.0163 < d < 0.0477 (5) | 4 | 4.30 |
| d < 0.0163 (6) | 40 | 43.01 |
| Inconsistent choices | 11 | 11.83 |
| Total | 93 | 100.00 |
| | | |
| **Longer time trade-off** | Freq. | Percent |
| d> 0.0915 (0) | 18 | 19.35 |
| 0.0726 < d < 0.0915 (1) | 2 | 2.15 |
| 0.0602 < d <0.0726 (2) | 4 | 4.30 |
| 0.0514< d <0.0602 (3) | 6 | 6.45 |
| 0.0275< d < 0.0514 (4) | 8 | 8.60 |
| 0.0059< d < 0.0275 (5) | 13 | 13.98 |
| d < 0.0059 (6) | 31 | 33.33 |
| Inconsistent choices | 11 | 11.83 |
| Total | 93 | 100.00 |

Consistency was checked during the experiment such that, once the delayed options were chosen by the respondents, in the first task, all the subsequent

choices had to be consistent with the initial one. For instance, concerning choice number 1 in table 2.6, consistency means that if a participant chooses the delayed pay-off in this task, e.g., 26, it is expected to select the delayed option in all the subsequent tasks since they involve the same time horizon (one month), the same short-term pay-off (25) but larger long-term pay-off (>26). Despite consistency being checked by the ELSA team during the experiment, some participants made this type of inconsistent choices. Therefore, we took the first consistent switching point for each participant pertaining to this category and subsequently assigned the same participants to the *low time preferences* category if the switching point felt below the cut-off value of four (included) or to the category of *high discount rate* if otherwise. For instance, as described in table 2.9 individual with id number 151 chose the delayed option twice (task 7 and task 8 respectively) before switching to the non-delayed option in task 9. This participant was counted as is if he chose the delayed option twice and therefore was assigned to the *high-discount rate* category.

**Table 2-9 Raw responses to the time preference tasks used to derive the longer time trade-off (1 signifies the non-delayed pay-off was chosen, 2 otherwise).**

| id | Longer time trade-off | Task 7 | Task 8 | Task 9 | Task 10 | Task 11 | Task 12 |
|---|---|---|---|---|---|---|---|
| 135 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 151 | Incon. | 2 | 2 | 1 | 1 | 2 | 2 |
| 157 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 327 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 383 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 616 | Incon. | 2 | 2 | 2 | 1 | 2 | 2 |
| 970 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 994 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 1057 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 1063 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 1332 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1355 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1900 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 2009 | 1 | 1 | 1 | 1 | 1 | 1 | 2 |
| 2190 | 2 | 1 | 1 | 1 | 1 | 2 | 2 |
| 2203 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 2383 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 2404 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 2512 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2561 | Incon. | 1 | 1 | 1 | 2 | 2 | 1 |
| 2604 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 2628 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 2653 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 2709 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 2848 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 2849 | 1 | 1 | 1 | 1 | 1 | 1 | 2 |
| 3012 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3097 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3342 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 3435 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 3447 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3456 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3731 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 3914 | Incon. | 2 | 1 | 1 | 1 | 1 | 2 |
| 3968 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4035 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 4195 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4292 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4329 | Incon. | 1 | 1 | 2 | 1 | 2 | 2 |
| 4416 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 4650 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 4689 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4703 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4709 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4744 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 5099 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 5199 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 5200 | Incon. | 2 | 2 | 2 | 2 | 2 | 1 |
| 5368 | Incon. | 1 | 1 | 1 | 1 | 2 | 1 |
| 5416 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 5534 | 2 | 1 | 1 | 1 | 1 | 2 | 2 |
| 5554 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 5615 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 5728 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 5817 | Incon. | 2 | 1 | 1 | 1 | 1 | 1 |
| 5841 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 5893 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 5991 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6006 | Incon. | 2 | 1 | 2 | 2 | 2 | 2 |
| 6126 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 6292 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6309 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6353 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 6370 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 6405 | 2 | 1 | 1 | 1 | 1 | 2 | 2 |
| 6516 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 6734 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 7347 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 7357 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 7706 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 7716 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 7724 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 7764 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 7896 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 7906 | Incon. | 2 | 2 | 1 | 2 | 2 | 1 |
| 7912 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 7968 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 8084 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 8276 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 8394 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 8506 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 8539 | 5 | 1 | 2 | 2 | 2 | 2 | 2 |
| 8557 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 8593 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 8623 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 8633 | 4 | 1 | 1 | 2 | 2 | 2 | 2 |
| 8678 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 8892 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 8922 | Incon. | 1 | 2 | 1 | 2 | 2 | 2 |
| 8941 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 8955 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 9069 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| 9242 | 2 | 1 | 1 | 1 | 1 | 2 | 2 |

Table 2.10 reports a table of frequencies count for the variable longer time trade off after the participants with inconsistent time preferences were categorised as previously described.

**Table 2-10 Tabulation of the variable longer time trade-off after taking the first switching point for the category of participants with inconsistent time preferences.**

| | Freq. | Percent |
|---|---|---|
| d> 0.0915 (0) | 18 | 19.35 |
| 0.0726 < d < 0.0915 (1) | 10 | 10.75 |
| 0.0602 < d <0.0726 (2) | 6 | 6.45 |
| 0.0514< d <0.0602 (3) | 7 | 7.53 |
| 0.0275< d < 0.0514 (4) | 8 | 8.60 |
| 0.0059< d < 0.0275 (5) | 13 | 13.98 |
| d < 0.0059 (6) | 31 | 33.33 |
| Total | 93 | 100.00 |

#### 2.2.3.4 Cross tabulation shorter and longer time trade- offs Type 2 diabetes sample.

Table 2.11 reports a cross tabulation of the two variables which describes time preferences e.g., shorter, and longer time trade-offs. The levels of the variables *shorter time trade-offs* are entered as rows and the levels of the variables *longer time trade-offs* are entered as columns. Therefore, each cell represents a distinctive combination of the level of the two variables. The total column instead represents the distribution of the variable longer time trade-offs whereas total row denotes the distribution of the variable shorter time trade-off.

**Table 2-11 Cross tabulation of shorter and longer time trade-offs for the T2DM sample.**

| Longer time trade-offs | Shorter time trade-offs | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | Total |
| 0 | 15 | 1 | 1 | 0 | 0 | 0 | 1 | 18 |
| 1 | 3 | 4 | 0 | 0 | 2 | 1 | 0 | 10 |
| 2 | 0 | 1 | 0 | 2 | 1 | 0 | 2 | 6 |
| 3 | 0 | 2 | 2 | 1 | 0 | 1 | 1 | 7 |
| 4 | 0 | 0 | 0 | 1 | 2 | 1 | 4 | 8 |
| 5 | 0 | 1 | 0 | 2 | 3 | 1 | 6 | 13 |
| 6 | 1 | 0 | 1 | 1 | 2 | 0 | 26 | 31 |
| Total | 19 | 9 | 4 | 7 | 10 | 4 | 40 | 93 |

### 2.2.3.5 Risk preference variable

The risk-preference variable was retrieved by the participant's responses to task number 2 of the risk preference module. The risk preferences module consisted of ten incentivised risk preference tasks wherein participants had to choose one token out of the six available to choose from. An example of a representative risk preference task, game number 2 precisely, is given in figure 2.1.

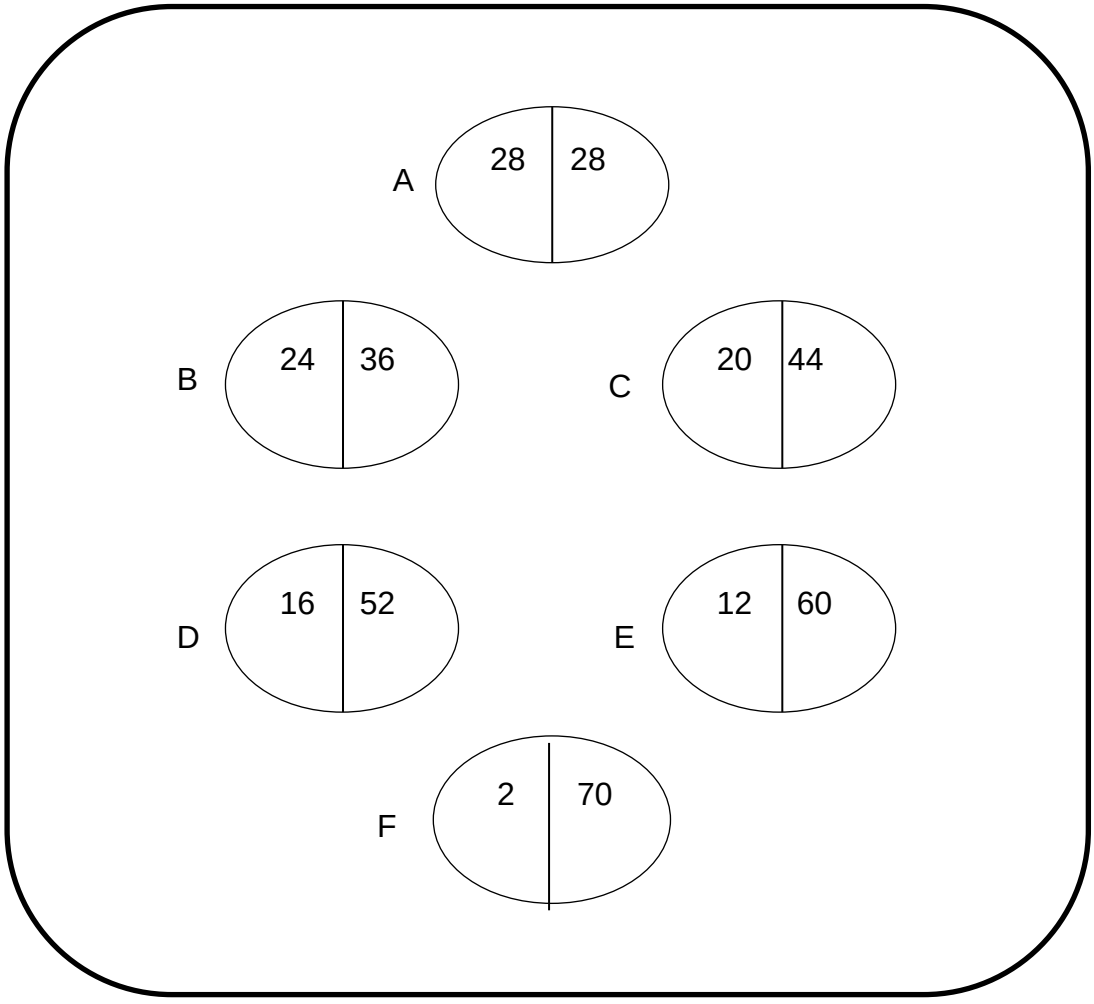


**Figure 2-1 Game number 2 from the risk preference task and its relative pay-offs from the ELSA risk-module**

Each token had an equal probability, e.g., 50% of turning either of its sides. However, a different pay-off was attached to each side of the token, as seen from the representative risk-preferences task (out of the ten in the risk module) shown

in figure 2.1. This figure intuitively suggests that each token bears a different level of risk. For example, if we compare tokens A and B together. It must be clear that token B bears a greater level of risk over token A considering its higher expected value [ (24 + 36)/2 = 30, the predicted value for the option B; (24 + 36 /2 = 30 the expected value for A].

**Table 2-12 Game number 2 of the risk-preference module, implied CRRA (ELSA) following the Eckel and Grossman approach.**

| **Task number 2 risk preference module** | **Token** | | | | | |
|---|---|---|---|---|---|---|
| | A (1) | B (2) | C(3) | D(4) | E(5) | F(6) |
| Payoffs (yellow/blue) | 28/28 | 24/36 | 20/44 | 16/52 | 12/60 | 2/70 |
| Expected Value | 28 | 30 | 32 | 34 | 36 | 36 |
| Standard Deviation | 0 | 6 | 12 | 18 | 24 | 34 |
| Implied CRRA(r)( | 3.46<r | 1.16<r<3.46 | 0.71<r<1.16 | 0.5<r<0.71 | 0<0.5 | r<0 |

Subsequently, the ELSA team calculated the coefficient of relative risk aversion (CRRA) for each participant simply by comparing their answer to task number 2 and the predetermined value calculated by Eckel and Grossman in their seminal work on eliciting risk preferences [81, 82]. No further information was included in the ELSA technical report for the risk module experiment on how to start from the participants' responses to task number 2, these values of the CRRA were calculated, and no further manipulation of the data was required in this sense. However, additional helpful information could be retrieved from the original Eckell and Grossman publication [81]. According to this approach, it can be inferred from Table 2.12 that gamble A does not bear any risk for the people who choose it. The pay-off is fixed and equal to 28 regardless of whether the coin turned either of its sides. All the remaining tasks bear different levels of risk as represented by the value of their standard deviation, e.g., higher standard deviation implies higher risk. It is worth noting that gamble E has the same expected pay-off as

gamble F (36) but a lower standard deviation, and consequently, it implies a lower level of risk (and higher value of the CRRA measured by *r*) compared to F.

Each task has been specifically designed so that risk-averse individuals should choose gambles with a lower standard deviation (A to D), risk-neutral should choose the stake with the higher expected pay-off (E), and risk-lovers should choose the gamble with the higher standard deviation (F). As already noted above, under the assumption of constant relative risk aversion and by comparing the answer to the second game to the Eckel-Grossman tasks [81], it was possible, for the ELSA team, to elicit an implied Coefficient of Constant Risk Aversion (CRRA) r for each of the respondents. If the CRRA assumption holds, the utility can be calculated by the following formula as suggested by Eckell and Grossman:

$$u(x) = x^{\wedge(1-r)}$$

with *r* representing the coefficient of relative risk-aversion and *x* wealth. According to this method, individuals with r > 0 can be classified as risk-averse, r<0 risk-lover, and r = 0 risk-neutral. Table 2.12 contains the intervals of *r* implied by each gamble. The intervals for *r* are calculated by determining the value *r*, which would make the individual indifferent by the bet they chose and the two adjacent gambles. For instance, let assume that an individual would have chosen gamble C, the value of r, which makes that individual indifferent between C and B, is 0.71. At the same time, indifference between C and D is obtained with a value of r of 1.17. This is a relatively simple method to elicit risk preferences. Compared to other more sophisticated and more complex methods, it was revealed to perform well in measuring individuals' attitudes towards risk, particularly for those with lower maths abilities [83, 84]. Participants in the final sample who reported a value of *r = 0* were classified as *risk-neutral*. Participants with a discount for *r > 0*

were categorised as *risk-averse*, while participants with a value of $r < 0$ as *risk-lovers*.

#### 2.2.3.6 Correlation between risk and time preferences variables – t2dm sample

A correlation between the risk and time preferences variables may be hypothesised, e.g., *risk lovers* have higher discount rates than *risk-neutral* individuals. Table 2.13 displays pairwise correlation coefficients and their relative *p-value* with a significance at or better than 5% level amongst these two variables for the T2DM only sample. Surprisingly, neither the *shorter* nor the *longer time-trade-offs* are correlated with the risk preferences variables adopted in the current analysis.

**Table 2-13 pairwise correlation coefficients between the risk and time preferences variable and its relative p-value with a significance at or better than 5% level.**

| | Shorter time trade-off | Risk preferences | | Longer time trade-off | Risk preferences |
|---|---|---|---|---|---|
| Shorter time trade-offs | 1.000 | | Longer time trade-offs | 1.000 | |
| Risk preferences | 0.067 (95% Cis; -0.138 to 0.267; p-value 0.526) | 1.000 | Risk preferences | 0.064 (95%Cis; -0.141 to 0.264; p-value 0.546) | 1.000 |

#### 2.2.3.7 Socio-demographic characteristics

Demographic characteristics include age divided into the two categories of participants from 50 to 70 years old and older than 70. Gender (divided into the categories of males and females), education (divided into the three categories of participants with no qualification, high school/a levels, college degree or higher) and quintiles of non-pension wealth as a measure for income (this last variable was incorporated only in the analysis which include participants with at least one chronic condition). All these variables have been chosen because they are

anticipated to influence investment in health as defined by the Grossman model and because they have been shown to be important determinants of adherence.

## 2.3 Results

### 2.3.1 Descriptive statistics

#### 2.3.1.1 Summary statistics for the Type 2 diabetes sample

Descriptive statistics for the final sample for each process of care (HbA1c, foot examination and blood pressure) are presented in tables 2.14, 2.15 and 2.16, respectively. In addition, each sample has been stratified into participants who adhered to that specific medical check (yes/no), and characteristics between these two groups have been compared with chi-squared test (significance level 0.05). No statistically significant difference was found among the socio-demographic characteristics between the two groups, e.g., participants who self-reported to have attended any of the checks compared to participants who did not self-reported to have attended. Similarly, these groups did not statistically differ in risk and time preferences (significance level p=0.05).

**Table 2-14 Summary statistics for the HbA1c check sample, tests for comparisons of the characteristics between the two groups (significance level 0.05).**

| | Hab1c check | | |
|---|---|---|---|
| | Yes | No | Test (p-value) |
| N = 93 | 67 (72.0%) | 26 (28.0%) | |
| Age (categorical) | | | |
| 50-70 | 45 (67.2%) | 20 (76.9%) | 0.357 |
| >70 | 22 (32.8%) | 6 (23.1%) | |
| Gender (male/female) | | | |
| Male | 40 (59.7%) | 12 (46.2%) | 0.238 |
| Female | 27 (40.3%) | 14 (53.8%) | |
| Education | | | |
| No qualification | 19 (28.4%) | 4 (15.4%) | 0.334 |
| College degree or higher | 47 (70.1%) | 22 (84.6%) | |
| Missing | 1 (1.5%) | 0 (0.0%) | |
| Non-pension wealth(quintiles) | | | |
| 1 | 12 (17.9%) | 6 (23.1%) | 0.382 |
| 2 | 16 (23.9%) | 2 (7.7%) | |
| 3 | 12 (17.9%) | 6 (23.1%) | |
| 4 | 13 (19.4%) | 5 (19.2%) | |
| 5 | 11 (16.4%) | 7 (26.9%) | |
| Missing | 3 (4.5%) | 0 (0.0%) | |
| Time preference | | | |
| Low discount rate | 31 (46.3%) | 13 (50.0%) | 0.746 |
| High discount rate | 36 (53.7%) | 13 (50.0%) | |
| Risk preference | | | |
| Risk-averse | 55 (82.1%) | 18 (69.2%) | 0.391 |
| Risk-neutral | 5 (7.5%) | 3 (11.5%) | |
| Risk-lovers | 7 (10.4%) | 5 (19.2%) | |

**Table 2-15 Summary statistics for the feet examination check sample, tests for comparisons of the characteristics between the two groups (significance level 0.05)**

| | Blood pressure check | | |
|---|---|---|---|
| | Yes | No | Test (p-value) |
| N = 93 | 87 (93.5%) | 6 (6.5%) | |
| Age (categorical) | | | |
| 50-70 | 59 (67.8%) | 6 (100.0%) | 0.096 |
| >70 | 28 (32.2%) | 0 (0.0%) | |
| Gender (male/female) | | | |
| Male | 47 (54.0%) | 5 (83.3%) | 0.162 |
| Female | 40 (46.0%) | 1 (16.7%) | |
| Education | | | |
| No qualification | 22 (25.3%) | 1 (16.7%) | 0.856 |
| College degree or higher | 64 (73.6%) | 5 (83.3%) | |
| Missing | 1 (1.1%) | 0 (0.0%) | |
| Non-pension wealth(quintiles) | | | |
| 1 | 17 (19.5%) | 1 (16.7%) | 0.352 |
| 2 | 18 (20.7%) | 0 (0.0%) | |
| 3 | 17 (19.5%) | 1 (16.7%) | |
| 4 | 16 (18.4%) | 2 (33.3%) | |
| 5 | 17 (19.5%) | 1 (16.7%) | |
| Missing | 2 (2.3%) | 1 (16.7%) | |
| Time preference | | | |
| Low discount rate | 41 (47.1%) | 3 (50.0%) | 0.892 |
| High discount rate | 46 (52.9%) | 3 (50.0%) | |
| Risk preference | | | |
| Risk-averse | 67 (77.0%) | 6 (100.0%) | 0.415 |
| Risk-neutral | 8 (9.2%) | 0 (0.0%) | |
| Risk-lovers | 12 (13.8%) | 0 (0.0%) | |

**Table 2-16 Summary statistics for the feet examination check sample, tests for comparisons of the characteristics between the two groups (significance level 0.05)**

| | Feet check | | |
|---|---|---|---|
| | Yes | No | Test (p-value) |
| N = 93 | 69 (74.2%) | 24 (25.8%) | |
| Age (categorical) | | | |
| 50-70 | 47 (68.1%) | 18 (75.0%) | 0.527 |
| >70 | 22 (31.9%) | 6 (25.0%) | |
| Gender (male/female) | | | |
| Male | 41 (59.4%) | 11 (45.8%) | 0.248 |
| Female | 28 (40.6%) | 13 (54.2%) | |
| Education | | | |
| No qualification | 19 (27.5%) | 4 (16.7%) | 0.458 |
| College degree or higher | 49 (71.0%) | 20 (83.3%) | |
| Missing | 1 (1.4%) | 0 (0.0%) | |
| Non-pension wealth(quintiles) | | | |
| 1 | 14 (20.3%) | 4 (16.7%) | 0.692 |
| 2 | 15 (21.7%) | 3 (12.5%) | |
| 3 | 12 (17.4%) | 6 (25.0%) | |
| 4 | 13 (18.8%) | 5 (20.8%) | |
| 5 | 12 (17.4%) | 6 (25.0%) | |
| Missing | 3 (4.3%) | 0 (0.0%) | |
| Time preference | | | |
| Low discount rate | 30 (43.5%) | 14 (58.3%) | 0.209 |
| High discount rate | 39 (56.5%) | 10 (41.7%) | |
| Risk preference | | | |
| Risk-averse | 56 (81.2%) | 17 (70.8%) | 0.402 |
| Risk-neutral | 6 (8.7%) | 2 (8.3%) | |
| Risk-lovers | 7 (10.1%) | 5 (20.8%) | |

#### 2.3.1.2 Summary statistics for the sample including all chronic conditions (T2DM, high-blood pressure or cholesterol)

There were 551 participants with at least one chronic condition (T2DM, high-blood pressure or cholesterol) in the final sample and their descriptive characteristics are presented in table 2.17 below. The category of people above the age of 70 was greater in the people who attended the blood pressure check over the past year (25.6 % compared to 11.7%, p-value< 0.01). No other statistically significant difference was found between the two groups of people who attend and did not attend the blood pressure check respectively. More than a half of the final sample is risk averse. The majority of the sample is risk averse with a higher proportion of individuals (77 % among the participant who attended the blood pressure check and 87.2% otherwise) who choose the gamble with the highest implied CRRA e.g., >3.47 compared to the participants who decided the option with a CRRA strictly minor than 0 (please refer to table 2.12 in the section which describe the construction of the risk preferences variable).

**Table 2-17 Summary statistics for the sample including all chronic conditions (T2DM, high-blood pressure or cholesterol), tests for comparisons of the characteristics between the two groups (significance level 0.05).**

| | Blood pressure check | | |
|---|---|---|---|
| | Yes | No | Test |
| N = 551 | 457 (82.9%) | 94 (17.1%) | |
| Age (categorical) | | | |
| 50-70 | 340 (74.4%) | 83 (88.3%) | 0.004 |
| >70 | 117 (25.6%) | 11 (11.7%) | |
| Gender (male/female) | | | |
| Male | 211 (46.2%) | 48 (51.1%) | 0.387 |
| Female | 246 (53.8%) | 46 (48.9%) | |
| Education | | | |
| No qualification | 103 (22.5%) | 24 (25.5%) | 0.771 |
| High school/A-levels | 273 (59.7%) | 52 (55.3%) | |
| College degree | 79 (17.3%) | 18 (19.1%) | |
| Missing | 2 (0.4%) | 0 (0.0%) | |
| Non-pension wealth(quintiles) | | | |
| 1 | 87 (19.0%) | 22 (23.4%) | 0.398 |
| 2 | 97 (21.2%) | 11 (11.7%) | |
| 3 | 91 (19.9%) | 18 (19.1%) | |
| 4 | 88 (19.3%) | 20 (21.3%) | |
| 5 | 87 (19.0%) | 21 (22.3%) | |
| Missing | 7 (1.5%) | 2 (2.1%) | |
| Time preference | | | |
| Low discount rate | 197 (43.1%) | 42 (44.7%) | 0.779 |
| High discount rate | 260 (56.9%) | 52 (55.3%) | |
| Risk preference | | | |
| Risk-averse | 352 (77.0%) | 82 (87.2%) | 0.077 |
| Risk-neutral | 51 (11.2%) | 7 (7.4%) | |
| Risk-lovers | 54 (11.8%) | 5 (5.3%) | |

*Note: t-tests for continuous variables and chi-squared tests for categorical variables were performed to test for differences between the two groups.*

### 2.3.2 Regression results

#### 2.3.2.1 Blood pressure, Hb1c and feet examination check in the T2DM sample.

Table 2.18., 2.19 and 2.20 report results (Odds Ratios and 95% CIs) from the binary logistic regressions, with each medical check as the dependent variable. Two variables describe the participants' time preferences. These variables are *shorter time trade-offs* (2 weeks vs 1 month) and *longer time trade-offs* (2 weeks vs 2 months). For clarity reasons and given its slightly more suitability as previously described, only models that included the *longer time trade-off* are presented in this section. In contrast, models with the *shorter time trade-off* are presented in the Appendix (A.3). After reviewing the literature to apprehend the study area and have a better understanding of which regressors to include, I have decided to estimate four model specifications in total for each dependent variable. I ran the model first (model 1) with the time preference variable *longer time trade-off* only as it pertains to the specific *a-priori* hypothesis that predicts participants with low discount rate to be more likely to adhere to the medical checks compared to their high-discount rate counterpart (hypothesis 1 in the section 2.1.2 about the objectives). Following a similar reasoning as before in model 2, I have included risk preferences only since, in line with hypothesis 2 it can be hypothesized that attitudes towards risk may affect adherence to the medical check for T2DM. Model 3 contains both the time and risk preference variables. In this model, I decided to include both time and risk preferences because they might be correlated as well as both influencing the outcome of interest. Therefore, jointly considering these two variables in the same model is important. To conclude, model 4 contains socio-demographics plus the time and risk preference variables. The socio-demographics characteristics (age, gender and education)

were included because of their well-established relationship with medical checks and health behaviour in general. The choice to include age and education among the covariates is also supported by the theoretical framework. The Grossman model suggests that people increase their investment in health as they age to offset the depreciation of their health stock. It also predicts that education will increase investment in health because it will raise the efficiency with which investments in health are produced, i.e., the more educated individuals would demand a more extensive optimal stock of health.

Overall, the results show no statistically significant association between time, risk preferences, and adherence to the medical checks for managing T2DM. While at times, the sign of the main variables of interest pointed in the hypothesised direction, which sees risk lovers to be less likely to adhere to the checks, as was the case for risk preference in the HbA1c and feet checks models as reported in table 2.19 and 2.20 respectively, at other time results are counterintuitive. For example, always from Table 2.18 the sign of the coefficient for the high discount rate group pointed in the opposite direction of what the *a-priori* expectation would have predicted. However, it did not reach statistical significance at the 5% level. In contrast, the coefficient for age displayed a positive sign for each outcome variable which aligns with the theoretical prediction of the Grossman model i.e., people are more willing to invest in their health as they age to counterbalance the depreciation of their initial health stock. However, the coefficient of age never reached statistical significance at the 5% level. The following section, 2.5 about the discussion will expand upon the possible reasons why the present analysis did not show any relationship between the medical checks for T2DM and time and risk preferences.

**Table 2-18 Penalized maximum likelihood estimates in the form of odds ratios for the T2DM sample with blood pressure check as the dependent variable.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| | | | | | | | | |
| Low discount rate *(ref.)* | | | | | | | | |
| High discount rate | 1.150 | [0.220,6.021] | | | 1.259 | [0.268,5.917] | 1.051 | [0.217,5.085] |
| Risk-averse *(ref.)* | | | | | | | | |
| Risk-neutral | | | 1.662 | [0.0858,32.19] | 1.818 | [0.0906,36.46] | 2.410 | [0.121,47.82] |
| Risk-lovers | | | 2.444 | [0.129,46.19] | 2.423 | [0.129,45.41] | 2.581 | [0.133,50.00] |
| 50-70 *(ref.)* | | | | | | | | |
| >70 | | | | | | | 5.493 | [0.290,104.1] |
| Male *(ref.)* | | | | | | | | |
| Female | | | | | | | 1.892 | [0.296,12.10] |
| No qualification (ref.) | | | | | | | | |
| High school/A-levels | | | | | | | 1.361 | [0.171,10.80] |
| College degree or higher | | | | | | | 0.734 | [0.0771,6.988] |
| Observations | 92 | | 92 | | 92 | | 92 | |
| Pseudo $R^2$ | 0.001 | | | | | | | |
| *AIC* | 48.33 | | 49.11 | | 50.51 | | 53.30 | |
| *BIC* | 53.38 | | 56.67 | | 60.60 | | 73.48 | |

Exponentiated regression coefficients; 95% confidence intervals in brackets. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit. Note: since penalised maximum likelihood does not permit the calculation of the pseudo $R^2$ therefore this statistic for the models 2,3 and 4 was not reported. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

**Table 2-19 Maximum likelihood estimates in the form of odds ratios for the T2DM sample with HbA1c check as the dependent variable.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Hab1c check | | Hab1c check | | Hab1c check | | Hab1c check | |
| | | | | | | | | |
| Low discount rate *(ref.)* | | | | | | | | |
| High discount rate | 1.200 | [0.484,2.977] | | | 1.163 | [0.457,2.959] | 1.017 | [0.379,2.726] |
| Risk-averse *(ref.)* | | | | | | | | |
| Risk-neutral | | | 0.556 | [0.121,2.559] | 0.581 | [0.123,2.747] | 0.630 | [0.122,3.251] |
| Risk-lovers | | | 0.467 | [0.132,1.654] | 0.464 | [0.131,1.648] | 0.617 | [0.165,2.304] |
| 50-70 *(ref.)* | | | | | | | | |
| >70 | | | | | | | 1.596 | [0.508,5.012] |
| Male *(ref.)* | | | | | | | | |
| Female | | | | | | | 0.440 | [0.159,1.216] |
| No qualification *(ref.)* | | | | | | | | |
| High school/A-levels | | | | | | | 0.536 | [0.143,2.008] |
| College degree or higher | | | | | | | 0.288 | [0.0590,1.405] |
| Observations | 92 | | 92 | | 92 | | 92 | |
| Pseudo $R^2$ | 0.001 | | 0.015 | | 0.016 | | 0.060 | |
| *AIC* | 113.4 | | 113.9 | | 115.8 | | 119.0 | |
| *BIC* | 118.4 | | 121.4 | | 125.8 | | 139.2 | |

Exponentiated regression coefficients; 95% confidence intervals in brackets. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

**Table 2-20 Maximum likelihood estimates in the form of odds ratio for the T2DM sample with feet examination as the dependent variable.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Feet check | | Feet check | | Feet check | | Feet check | |
| Feet check | | | | | | | | |
| Low discount rate *(ref.)* | | | | | | | | |
| High discount rate | 1.883 | [0.733,4.835] | | | 1.984 | [0.753,5.233] | 1.811 | [0.648,5.057] |
| Risk-averse *(ref.)* | | | | | | | | |
| Risk-neutral | | | 0.927 | [0.171,5.026] | 1.134 | [0.202,6.359] | 1.293 | [0.213,7.855] |
| Risk-lovers | | | 0.433 | [0.122,1.541] | 0.415 | [0.114,1.509] | 0.526 | [0.135,2.050] |
| 50-70 *(ref.)* | | | | | | | | |
| >70 | | | | | | | 1.507 | [0.455,4.994] |
| Male *(ref.)* | | | | | | | | |
| Female | | | | | | | 0.394 | [0.133,1.166] |
| No qualification (ref.) | | | | | | | | |
| High school/A-levels | | | | | | | 0.791 | [0.202,3.106] |
| College degree or higher | | | | | | | 0.246 | [0.0487,1.245] |
| Observations | 92 | | 92 | | 92 | | 92 | |
| Pseudo $R^2$ | 0.017 | | 0.015 | | 0.034 | | 0.090 | |
| *AIC* | 107.9 | | 110.0 | | 110.0 | | 112.1 | |
| *BIC* | 112.9 | | 117.6 | | 120.1 | | 132.3 | |

Exponentiated regression coefficients; 95% confidence intervals in brackets $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

#### 2.3.2.2 Blood pressure check for the sample including all the participants with at least one chronic condition (T2DM, high blood-pressure, high cholesterol)

Table 2.21 reports the results for the sample, which included the participants, diagnosed with at least any of the following chronic conditions: T2DM, high cholesterol or high blood pressure. Time and risk preferences still did not reach statistical significance. Moreover, the results for risk preference were ambiguous and in the opposite direction of what the theoretical framework would have predicted, suggesting that risk-neutral and risk-lover participants are more likely to adhere to the blood pressure check than their risk-averse equivalent. Among the covariates, age increases investment in health in line with the predictions of the theoretical framework i.e., individuals are more likely to invest in their health as they age. The odds to adhere with the blood pressure check were greater for the group of participants above the age of 70 compared to their 50 to 70 equivalents (Odds Ratios 2.623, p-value <0.001). Despite education increased the odds to comply with the blood pressure check in line with the expectations suggested by the theoretical framework, this variable did not reach statistical significance (p-value <0.05). No effect for gender and income were detected.

**Table 2-21 Maximum likelihood estimates in the form of odds ratios for the sample including participants diagnosed with at least one chronic condition with blood pressure as the dependent variable.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Blood pressure check | | | | | | | | |
| Low discount rate | | | | | | | | |
| High discount rate | 1.007 | [0.641,1.584] | | | 1.035 | [0.657,1.633] | 0.970 | [0.606,1.554] |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | 1.962 | [0.813,4.734] | 1.965 | [0.814,4.742] | 2.132 | [0.872,5.214] |
| Risk-lovers | | | 2.543 | [0.986,6.560] | 2.549 | [0.988,6.580] | 2.491 | [0.951,6.524] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.623** | [1.325,5.189] |
| Male | | | | | | | | |
| Female | | | | | | | 1.172 | [0.737,1.866] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.412 | [0.787,2.535] |
| College degree or higher | | | | | | | 1.408 | [0.636,3.115] |
| Non pension wealth *(1 ref.)* | | | | | | | | |
| 2 | | | | | | | 1.995 | [0.900,4.423] |
| 3 | | | | | | | 1.117 | [0.547,2.279] |
| 4 | | | | | | | 0.934 | [0.446,1.956] |
| 5 | | | | | | | 0.880 | [0.421,1.837] |
| Observations | 540 | | 540 | | 540 | | 540 | |
| Pseudo $R^2$ | 0.000 | | 0.013 | | 0.013 | | 0.045 | |
| *AIC* | 497.0 | | 492.4 | | 494.4 | | 494.6 | |
| *BIC* | 505.6 | | 505.3 | | 511.5 | | 546.1 | |

Exponentiated regression coefficients; 95% confidence intervals in bracket * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

#### 2.3.2.3 Robustness check: blood pressure checks for the sample which include all the participants in the wave 5 time and risk preference module.

An additional analysis was performed where all the participants who took part in the wave 5 time and risk preference module were included in the final sample regardless of whether they were diagnosed with any chronic condition. The aim of this additional robustness check was to ascertain that the issue related to statistical power could be the reason behind non statistically significant results rather than a genuine lack of a relationship between time and risk preference and adherence to the medical check for the management of T2DM. Results from this additional analysis are presented in Table 2.22 below. The selection of the blood pressure check as the main dependent variable is based on the Mayo Clinic's recommendation [85] that all adults over 40 receive this medical examination at least once a year. This assessment is particularly recommended for individuals above 50. As the average age of the sample is 63 years, it is important for this population to have their blood pressure checked at least once annually, irrespective of any chronic health issue. Results are expressed in terms of odds ratios. Even if the sample size increased considerably to 890 participants, there is still no statistically significant relationship between preference and adherence. As it was the case for the sample with all the participants diagnosed with at least one chronic condition, age increases the likelihood of adhering to the check for blood pressure in all the model specifications. For example, in model 4, the category of the participants above 70 years of age has greater odds of adhering to the medical check for blood pressure compared to their 50 to 70 equivalents (Odds Ratio 2.768, p-value <0.05). This effect is consistent in terms of both sign and magnitude in all the subsequent models.

**Table 2-22 Maximum likelihood estimates in the form of odds ratios for the sample including all the participants who took part in the wave 5 risk preference module with blood pressure check as the dependent variable.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Bp check | | Bp check | | Bp check | | Bp check | |
| Low discount rate | | | | | | | | |
| High discount rate | 0.793 | [0.510,1.234] | | | 0.794 | [0.510,1.237] | 0.748 | [0.476,1.177] |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | 1.004 | [0.483,2.087] | 0.987 | [0.474,2.054] | 0.992 | [0.472,2.082] |
| Risk-lovers | | | 1.140 | [0.569,2.285] | 1.128 | [0.562,2.262] | 1.089 | [0.539,2.202] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.768* | [1.236,6.199] |
| Male | | | | | | | | |
| Female | | | | | | | 1.067 | [0.682,1.670] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.289 | [0.690,2.406] |
| College degree or higher | | | | | | | 0.789 | [0.380,1.635] |
| 1 | | | | | | | | |
| 2 | | | | | | | 0.965 | [0.465,2.005] |
| 3 | | | | | | | 0.936 | [0.457,1.919] |
| 4 | | | | | | | 0.802 | [0.391,1.641] |
| 5 | | | | | | | 1.148 | [0.530,2.485] |
| Observations | 890 | | 890 | | 890 | | 890 | |
| Pseudo $R^2$ | 0.002 | | <0.001 | | 0.002 | | 0.024 | |
| *AIC* | 581.6 | | 584.5 | | 585.5 | | 588.7 | |
| *BIC* | 591.2 | | 598.9 | | 604.6 | | 646.2 | |

Exponentiated regression coefficients; 95% confidence intervals in brackets* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

#### 2.3.2.4 Sensitivity checks of results to different categorizations of the time and risk preferences variables.

Considering that both the time and risk preferences variables are categorised, a series of sensitivity checks was conducted to test the sensitivity of the results to the different categorisations. In the first sensitivity analysis, table 2.23, the variable describing time preferences was included as a continuous variable indicating the total number of delayed options chosen by the respondents in the six tasks used to derive the longer time trade off. As it was the case for the main analysis, the last consistent switching point for the category of participants with inconsistent time preferences was taken. Results did not differ compared to the main analysis. In the second sensitivity analysis, table 2.24, the variable longer *time trade off* was categorised in a different way compared to the primary analysis. Participants who chose the delayed options 4 time or more (instead of 5 times or more as it was done in the main analysis) were assigned to the low-discount rate category. This increased the proportion of individuals pertaining to the low-discount category which are now most of the sample (57.78%). This sensitivity check was conducted because recoding participants who made inconsistent choices increased the relative proportion of individuals pertaining to the category with high discount rates. Even in this case, result did not differ substantially compared to the principal analysis. In the third sensitivity analysis, the 47 participants who made inconsistent choices were excluded from the sample table 2.25. Still the main findings did not change compared to the previous analysis. In the fourth sensitivity check, table 2.26, the variable describing the participants time preference was dichotomised at the median value of its distribution. Finally, in the last sensitivity check Table 2.27 also the variable describing risk preference was dichotomised always at the median value.

Therefore, only two categories (instead of the usual three) for the risk preference variable were created i.e., risk averse and risk lovers. An effect for risk preferences was detected in model 3, indicating that risk lovers' participants to be more likely to adhere with the blood pressure check compares to their risk-averse counterpart (Odds Ratio 1.934; 95% CIs 1.120,3.117). This effect, which is in the opposite direction of what has been originally hypothesised, persisted in terms of sign and magnitude in models 3 and 4. While this effect might seem counterintuitive it is not a completely novel finding in the literature which is looking at the relationship between risk preference and adherence to medical check, as it will be described in more detail in the discussion.

**Table 2-23 Regression results for the first sensitivity analysis for time preferences. Time preference is treated as a continuous variable.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Blood pressure check | | | | | | | | |
| Time preference | | | | | | | | |
| 1 | 1.463 | [0.453,4.728] | | | 1.329 | [0.408,4.325] | 1.114 | [0.334,3.723] |
| 2 | 0.699 | [0.304,1.611] | | | 0.722 | [0.313,1.669] | 0.726 | [0.307,1.717] |
| 3 | 0.948 | [0.358,2.510] | | | 0.821 | [0.306,2.200] | 0.917 | [0.332,2.531] |
| 4 | 0.976 | [0.438,2.173] | | | 0.932 | [0.416,2.084] | 0.950 | [0.412,2.190] |
| 5 | 0.850 | [0.386,1.874] | | | 0.794 | [0.358,1.760] | 0.878 | [0.385,2.002] |
| 6 | 0.998 | [0.505,1.972] | | | 0.940 | [0.474,1.866] | 0.988 | [0.484,2.016] |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | 1.962 | [0.813,4.734] | 1.930 | [0.797,4.674] | 2.089 | [0.852,5.122] |
| Risk-lovers | | | 2.543 | [0.986,6.560] | 2.525 | [0.971,6.565] | 2.446 | [0.927,6.456] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.569** | [1.288,5.126] |
| Male | | | | | | | | |
| Female | | | | | | | 1.169 | [0.733,1.866] |
| No qualification ( | | | | | | | | |
| High school/A-levels | | | | | | | 1.420 | [0.788,2.558] |
| College degree or higher | | | | | | | 1.463 | [0.657,3.257] |
| Non pension wealth *(1 ref)* | | | | | | | | |
| 2 | | | | | | | 2.003 | [0.899,4.459] |
| 3 | | | | | | | 1.121 | [0.547,2.297] |
| 4 | | | | | | | 0.923 | [0.438,1.947] |
| 5 | | | | | | | 0.882 | [0.419,1.857] |
| Observations | 540 | | 540 | | 540 | | 540 | |
| Pseudo $R^2$ | 0.004 | | 0.013 | | 0.016 | | 0.047 | |
| *AIC* | 505.2 | | 492.4 | | 503.0 | | 503.8 | |
| *BIC* | 535.2 | | 505.3 | | 541.6 | | 576.8 | |

Exponentiated regression coefficients; 95% confidence intervals in brackets* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

**Table 2-24 Regression results for the second sensitivity analysis for time preferences. Participants who chose the delayed options 5 times or more were assigned to the low-discount rate category.**

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Blood pressure check | | | | | | | | |
| Low discount rate | | | | | | | | |
| High discount rate | 0.992 | [0.630,1.562] | | | 1.019 | [0.645,1.610] | 0.958 | [0.593,1.547] |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | 1.962 | [0.813,4.734] | 1.965 | [0.814,4.745] | 2.131 | [0.872,5.211] |
| Risk-lovers | | | 2.543 | [0.986,6.560] | 2.545 | [0.986,6.567] | 2.493 | [0.952,6.525] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.628** | [1.327,5.204] |
| Male | | | | | | | | |
| Female | | | | | | | 1.173 | [0.737,1.866] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.409 | [0.785,2.529] |
| College degree or higher | | | | | | | 1.404 | [0.634,3.109] |
| Non pension wealth *(1 ref.)* | | | | | | | | |
| 2 | | | | | | | 1.989 | [0.896,4.415] |
| 3 | | | | | | | 1.113 | [0.545,2.276] |
| 4 | | | | | | | 0.929 | [0.441,1.957] |
| 5 | | | | | | | 0.876 | [0.418,1.835] |
| Observations | 540 | | 540 | | 540 | | 540 | |
| Pseudo $R^2$ | 0.000 | | 0.013 | | 0.013 | | 0.045 | |
| *AIC* | 497.0 | | 492.4 | | 494.4 | | 494.6 | |
| *BIC* | 505.6 | | 505.3 | | 511.6 | | 546.1 | |

Odds ratios; 95% confidence intervals in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

**Table 2-25 Regression results for the third sensitivity analysis for time preferences. Participants with inconsistent time preferences were removed from the final sample.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Blood pressure check | | | | | | | | |
| Low discount rate | | | | | | | | |
| High discount rate | 0.937 | [0.581,1.513] | | | 0.968 | [0.598,1.567] | 0.937 | [0.565,1.555] |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | 1.752 | [0.720,4.263] | 1.745 | [0.716,4.254] | 1.880 | [0.758,4.663] |
| Risk-lovers | | | 2.341 | [0.902,6.077] | 2.337 | [0.900,6.068] | 2.334 | [0.881,6.183] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 3.263** | [1.495,7.124] |
| Male | | | | | | | | |
| Female | | | | | | | 1.180 | [0.728,1.913] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.577 | [0.853,2.913] |
| College degree or higher | | | | | | | 1.607 | [0.702,3.679] |
| Non pension wealth *(1 ref.)* | | | | | | | | |
| 2 | | | | | | | 2.403* | [1.019,5.671] |
| 3 | | | | | | | 1.084 | [0.509,2.307] |
| 4 | | | | | | | 0.892 | [0.416,1.911] |
| 5 | | | | | | | 0.869 | [0.404,1.869] |
| Observations | 493 | | 493 | | 493 | | 493 | |
| Pseudo $R^2$ | 0.000 | | 0.011 | | 0.011 | | 0.056 | |
| *AIC* | 460.3 | | 457.4 | | 459.4 | | 455.0 | |
| *BIC* | 468.7 | | 470.0 | | 476.2 | | 505.4 | |

Odds ratios; 95% confidence intervals in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

**Table 2-26 regression results for the fourth sensitivity analysis for time preferences. Time preference was dichotomised at the median value of its distribution.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Blood pressure check | | | | | | | | |
| Low discount rate | | | | | | | | |
| High discount rate | 1.007 | [0.641,1.584] | | | 1.035 | [0.657,1.633] | 0.970 | [0.606,1.554] |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | 1.962 | [0.813,4.734] | 1.965 | [0.814,4.742] | 2.132 | [0.872,5.214] |
| Risk-lovers | | | 2.543 | [0.986,6.560] | 2.549 | [0.988,6.580] | 2.491 | [0.951,6.524] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.623** | [1.325,5.189] |
| Male | | | | | | | | |
| Female | | | | | | | 1.172 | [0.737,1.866] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.412 | [0.787,2.535] |
| College degree or higher | | | | | | | 1.408 | [0.636,3.115] |
| Non pension wealth *(1 ref.)* | | | | | | | | |
| 2 | | | | | | | 1.995 | [0.900,4.423] |
| 3 | | | | | | | 1.117 | [0.547,2.279] |
| 4 | | | | | | | 0.934 | [0.446,1.956] |
| 5 | | | | | | | 0.880 | [0.421,1.837] |
| Observations | 540 | | 540 | | 540 | | 540 | |
| Pseudo $R^2$ | 0.000 | | 0.013 | | 0.013 | | 0.045 | |
| *AIC* | 497.0 | | 492.4 | | 494.4 | | 494.6 | |
| *BIC* | 505.6 | | 505.3 | | 511.5 | | 546.1 | |

Odds ratios; 95% confidence intervals in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

**Table 2-27 Regression results for the sensitivity analysis for risk preference. Risk preference was dichotomised at the median value of its distribution.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Blood pressure check | | | | | | | | |
| Low discount rate *(ref.)* | | | | | | | | |
| High discount rate | 1.007 | [0.641,1.584] | | | 1.007 | [0.639,1.589] | 0.931 | [0.581,1.492] |
| Risk-averse (ref.) | | | | | | | | |
| Risk-lovers | | | 1.934** | [1.200,3.117] | 1.934** | [1.200,3.117] | 1.999** | [1.227,3.257] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.612** | [1.318,5.174] |
| Male | | | | | | | | |
| Female | | | | | | | 1.250 | [0.783,1.994] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.465 | [0.814,2.637] |
| College degree or higher | | | | | | | 1.475 | [0.664,3.274] |
| Non pension wealth *(1 ref.)* | | | | | | | | |
| 2 | | | | | | | 1.962 | [0.884,4.358] |
| 3 | | | | | | | 1.062 | [0.518,2.175] |
| 4 | | | | | | | 0.897 | [0.429,1.877] |
| 5 | | | | | | | 0.886 | [0.422,1.859] |
| Observations | 540 | | 540 | | 540 | | 540 | |
| Pseudo $R^2$ | 0.000 | | 0.016 | | 0.016 | | 0.048 | |
| *AIC* | 497.0 | | 489.3 | | 491.3 | | 491.2 | |
| *BIC* | 505.6 | | 497.9 | | 504.2 | | 538.4 | |

Odds ratios; 95% confidence intervals in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

#### 2.3.2.5 Sensitivity that included an interaction between time preferences and T2DM and between risk preferences and T2DM.

Two additional sets of regressions were conducted in the current sensitivity analysis to explore further the relationship between time and risk preferences and adherence in people living with T2DM. In the first set of regression Table 2.28, four models were estimated, and the following list of covariates were included for each model: (1) an interaction term between time preferences and T2DM only; (2) an interaction term between risk preference and T2DM; (3) an interaction term between time preferences and T2DM plus the risk preference variable; (4) an interaction term between time preferences and T2DM, the risk preference variable plus the sociodemographic characteristics. In the second set of regressions Table 2.29, two additional models were calculated, and the order of the covariates was as follows: (1) an interaction term between risk preference and T2DM plus the time preferences variables; 2) an interaction term between risk preferences and T2DM, the time preference variable plus the sociodemographic characteristics. The results from the analysis, which included an interaction term between time and risk preferences and T2DM, were similar to the previous ones. An effect was detected for time and risk preferences for the category of people with T2DM and high discount rate (Odds Ratio 3.439, 95 Cis 1.012,11.69, $p<0.05$) and risk-averse individuals with T2DM (Odds Ratio 2.367, 95%CIs 1.041,5.380, $p<0.05$) in models 1 and 2 respectively Table 2.28 A statistically significant coefficient for the interaction term denotes that the impact of time and risk preference upon the outcome variable, e.g. the likelihood of attending the blood pressure check, varied among participants with and without T2DM. One possibility is that participants with T2DM are more likely to comply

with the blood pressure check regardless of the level of their time and risk preferences. Another is that people with T2DM have a higher time preference rate and are more risk-tolerant than people who did not develop the condition. However, the effects of the interaction terms were only significant at the 5% level and disappeared after adjusting for the covariates, as indicated by model 4. The fact that the interaction terms were no longer significant after adjusting for the sociodemographic characteristics suggests that time and risk preferences may be related to these characteristics. In other words, the sociodemographic characteristics absorb the effect of the time and risk preferences variables. A similar pattern was observed for the second set of regressions, as illustrated by Table 2.29.

**Table 2-28 Regression results for the analysis with an interaction term between time and risk preferences and T2DM with blood pressure as the dependent variable. First set of regressions.**

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| main | | | | | | | | |
| Low discount rate # no T2DM (*ref.)* | | | | | | | | |
| Low discount rate # T2DM | 2.121 | [0.711,6.330] | | | 2.124 | [0.708,6.365] | 2.088 | [0.686,6.359] |
| High discount rate # no T2DM | 0.978 | [0.607,1.577] | | | 1.004 | [0.621,1.624] | 0.947 | [0.576,1.556] |
| High discount rate # T2DM | 3.439* | [1.012,11.69] | | | 3.564* | [1.044,12.16] | 3.100 | [0.895,10.73] |
| Risk-averse # no T2DM *(ref.)* | | | | | | | | |
| Risk-averse # T2DM | | | 2.367* | [1.041,5.380] | | | | |
| Risk-neutral # no T2DM | | | 1.885 | [0.773,4.595] | | | | |
| Risk-neutral # T2DM | | | 3.966 | [0.224,70.23] | | | | |
| Risk-lovers # no T2DM | | | 2.209 | [0.845,5.777] | | | | |
| Risk-lovers # T2DM | | | 6.609 | [0.387,112.9] | | | | |
| Risk-averse | | | | | | | | |
| Risk-neutral | | | | | 2.053 | [0.848,4.967] | 2.201 | [0.898,5.393] |
| Risk-lovers | | | | | 2.489 | [0.960,6.452] | 2.440 | [0.926,6.428] |
| 50-70 | | | | | | | | |
| >70 | | | | | | | 2.478** | [1.246,4.928] |
| Male | | | | | | | | |
| Female | | | | | | | 1.222 | [0.764,1.954] |
| No qualification | | | | | | | | |
| High school/A-levels | | | | | | | 1.439 | [0.794,2.606] |
| College degree or higher | | | | | | | 1.422 | [0.634,3.191] |
| No pension wealth (1 ref.) | | | | | | | | |
| 2 | | | | | | | 1.929 | [0.864,4.310] |
| 3 | | | | | | | 1.069 | [0.519,2.203] |
| 4 | | | | | | | 0.921 | [0.435,1.947] |
| 5 | | | | | | | 0.855 | [0.404,1.811] |
| Observations | 540 | | 540 | | 540 | | 540 | |
| Pseudo $R^2$ | 0.016 | | | | 0.029 | | 0.059 | |
| *AIC* | 493.2 | | 488.5 | | 490.6 | | 492.0 | |
| *BIC* | 510.4 | | 514.2 | | 516.3 | | 552.1 | |

Odds ratios; 95% confidence intervals in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

**Table 2-29 Regression results for the analysis with an interaction term between time and risk preferences and T2DM with blood pressure as the dependent variable. Second set of regressions.**

| Model | (1) | | (2) | |
|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | |
| | | | | |
| Low discount rate # no T2DM *(ref.)* | | | | |
| Low discount rate # T2DM | | | | |
| High discount rate # no T2DM | | | | |
| High discount rate # T2DM | | | | |
| Risk-averse # no T2DM *(ref.)* | | | | |
| Risk-averse # T2DM | 2.366* | [1.041,5.377] | 2.203 | [0.964,5.037] |
| Risk-neutral # no T2DM | 1.884 | [0.773,4.590] | 2.000 | [0.815,4.909] |
| Risk-neutral # T2DM | 4.027 | [0.227,71.50] | 4.320 | [0.241,77.56] |
| Risk-lovers # no T2DM | 2.217 | [0.847,5.798] | 2.138 | [0.807,5.665] |
| Risk-lovers # T2DM | 6.598 | [0.386,112.7] | 6.126 | [0.355,105.7] |
| Low discount rate | | | | |
| High discount rate | 1.054 | [0.668,1.663] | 0.987 | [0.619,1.575] |
| 50-70 | | | | |
| >70 | | | 2.396* | [1.225,4.689] |
| Male | | | | |
| Female | | | 1.214 | [0.765,1.927] |
| No qualification | | | | |
| High school/A-levels | | | 1.410 | [0.788,2.525] |
| College degree or higher | | | 1.385 | [0.627,3.058] |
| 1 | | | | |
| 2 | | | 1.874 | [0.854,4.110] |
| 3 | | | 1.058 | [0.521,2.150] |
| 4 | | | 0.921 | [0.441,1.922] |
| 5 | | | 0.857 | [0.410,1.789] |
| Observations | 540 | | 540 | |
| Pseudo R2 | 0.0186 | | 0.048 | |
| AIC | 487.5 | | 470.0 | |
| BIC | 517.6 | | 534.4 | |

Odds ratios; 95% confidence intervals in brackets $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. Pseudo r-squared, Akaike information (AIC), and Bayesian information criterion (BIC) have been included as measures of Goodness of Fit.

## 2.4 Discussion

The present analysis investigated the hypothesis that time and risk preferences may partly explain adherence to the medical check for managing T2DM. The results found no association between the proxy for adherence to the annual care processes for managing type 2 diabetes available in ELSA main questionnaire and measurements for time preferences elicited during the experimental module in wave 5. However, even if not significant, the direction of the sign is consistent with the *a priori* hypothesis, but only in the models with blood -pressure check as the dependent variable (both in the T2DM only sample and in the sample which also included participants with high cholesterol and high blood pressure). These models predicted that participants with a high discount rate to be slightly less likely to comply with the annual medical checks for T2DM management. These findings are robust to several model specifications and different categorisation of the time preferences variable. What is more they are in line with previous research by Sloan et al., 2019 which reported no significant relationship between time preference and adherence to T2DM care practices, including HbA1c and cholesterol testing over the past year in people living with T2DM using data from the HRS [27]. Their regression models were also adjusted for risk preferences.

All else being equal (education, income), age increases investment in health in the direction suggested by the theoretical framework i.e., older participants more likely to adhere to the medical check for T2DM management. These findings persisted even after controlling for time and risk preferences. Moreover, they are consistent with part of the previous literature on the topic which found that after controlling for time and risk preferences (in addition to gender and education among the other covariates) people age 60 or more were more likely to adhere

to preventative aspirin use compared to the 40 to 60 age group (ORs 1.98; 95 CIs 1.16-3.21, p-value <0.001)[41]. As it was originally hypothesised, education also increases investment in health in a way like age, albeit to a lesser extent. A finding that aligns with research from Sloan et al. 2009 which always using the Grossman model as an underlying theoretical framework, found a positive association between education and adherence to the recommended care in people living with T2DM i.e. the more educated people were more likely follow T2DM recommended care [27]. Other research [18] also supports this empirical finding and highlighted that the more educated women were more likely to undergo testing (mammogram and Pap smear). However, in the present research, the coefficient for education never reached statistical significance at 5% level.

An association between time and risk preference and adherence was found; however, this was only detected in final sensitivity analyses when the risk preference variable was dichotomised or when an interaction term between preferences and T2DM was added among the covariates. Therefore, extreme caution is needed in interpreting these results. What is more, the association found when risks preferences were dichotomised, pointed in the opposite direction to what was originally hypothesised and saw risk-lovers participants be more likely to undertake the blood pressure check than their risk-averse equivalent. While this finding might seem counterintuitive, it is in line with some of the previous literature on the topic which showed that the less risk averse individuals were more likely undergo medical screening (an index which included breast self-exam, mammograms and Pap smear) [18].

Overall, the conclusions from the present analysis align with other studies that investigated a similar hypothesis and could not find any relationship between

preferences and adherence or, in some instances, a very modest association [27]. There could be several explanations, as will be outlined below.

First: research suggests that although time preferences may be a good predictor for adherence, present-biasedness (e.g., time-inconsistent discounting) appear to be the primary driver of unhealthy behaviour, rather than genuine variations in individuals' time preferences [26]. Present biasedness is the tendency to prefer smaller immediate rewards over more valuable but more distant (and unsure) ones [26, 36]. The quasi-hyperbolic utility function usually captures this kind of intertemporal preference [26, 36]. However, time preferences calculated during the experiment assumed a linear utility function. Therefore, given the nature and underlying assumptions of the experiment through which time preferences were elicited during the ELSA risk module, it was not possible to test the relationship between present biasedness and adherence. Second, the time horizon embedded in the time preference variables was too short. One or two months are probably insufficient to capture the relationship between preference and the insurgence of T2DM related long-term complications. Studies that found an association between time preference and health behaviour (including adherence) used longer time horizons of at least six months and up to one or more years [18, 21, 25]. Research suggests that time discounting in the health domain is strongly related to the length of the delay in the payoff of health behaviour [86]. Therefore, if the benefit arising from investment in health take several years to be realized, individuals with a relatively low life expectancy compared to the delay required to see these benefits may not consider returns from such long-term investments in their decision making [27]. This, especially, could be the case for an older age group like the one in the ELSA. For example, findings from the UKPDS study group indicates that lower HbA1c may take up to several years to provide tangible

benefits from an individual perspective [87]. Third, the sample size, albeit considerable, might still not hold sufficient statistical power and could be another plausible explanation behind these non-significant results. On average, studies that found an association between preferences and adherence relied on considerably larger sample sizes of several hundred if not thousands of participants [25, 40, 64, 88]. Although both newly and previously diagnosed participants were included in the analyses and observations were combined across three different waves to retain as many participants from the experimental module as possible, this did not reveal as sufficient. What is more, to increase statistical power participants who reported to have other chronic conditions other than that T2DM, such as hypertension or high cholesterol and for which to test the same hypothesis is a reasonable assumption were also included in the sample. An additional robustness checks increased statistical power even further by including all the participant with complete information on covariates who took part in the ELSA risk module. However, despite this effort the lack of association between preference and adherence persisted, with the only exception of risk preference in the last sensitivity analysis.

Fourth, another likely reason for the absence of time and risk preferences on the blood pressure check is the lack of variability among the dependent variable, which had only 6 negative responses.

Fifth, another possible explanation for these negative findings could be sample self-selection, e.g., people with diabetes have similar characteristics and behave similarly. However, T2DM is a widespread condition, which affects the general population, and this effect is likely to be minor compared to the lack of statistical power mentioned above. Sixth, another point to consider, that we could not have the possibility to explore due to the fact that the potential measures for the

duration of T2DM had large amounts of missing data, could be that most of the sample were individuals in their early stage of T2DM. Therefore, they lack the necessary skills to manage their condition proactively.

Seventh, the evidence on whether preferences elicited through the monetary domain can be applied whether preferences elicited from the monetary domains also apply to the health domain is mixed [89] [90]. However, a recent study in Denmark supported the idea that time preferences elicited in the monetary domain could be applied to the health domain[76].

To conclude this section, a significant limitation that needs to be acknowledged is that adherence to the guidelines for T2DM management does not entirely depend on patients' choices but also on GPs [91, 92]. If a practice has T2DM specialists, it is more likely that patients would receive reviews than the practice that does not have the same skill mix in their workforce. Large-scale incentives schemes like the Quality Outcome Framework (QOF) may also influence adherence to medical checks, given that the T2DM statement was a specific domain assessed during the QOF [93]. These incentive schemes may affect in a heterogeneous way across different practices and geographical locations. While the evidence established that adherence to T2DM checks increases with incentives and again decreases by almost the same amount once the incentives are removed, there might be more reactive practices than others to this kind of incentive. However, all these supply-side influences were well beyond the scope of the present research, which instead focused exclusively on the demand side determinants of adherence.

Regarding the strength of this study, it is worth mentioning that the measurement for the risk and time preference used in this paper were elicited through a laboratory experiment. Furthermore, the experiment also used monetary

incentives, which demonstrated to perform well in capturing individuals' intertemporal preferences and attitudes towards risk. On the contrary, most of the studies in this area rely on proxies for the risk and time preferences, or at best small laboratories experiment (usually involving students). On the one hand, using proxies for preferences, like planning horizon, often involves hypothetical choices that can lead to hypothetical bias. On the other hand, small laboratories experiment could not be very representative of the general population. Incentivised choice experiments like the one we exploited in this study performed well in predicting individuals' actual behaviour. In addition, the participants' profile to the ELSA risk experiment fits very well the population of interest considering that complications from diabetes tend to develop in older age.

## 2.5 Conclusions

Although time and risk preferences revealed to be a promising framework in some context to support policies aimed at increasing adherence and empowering people living with T2DM to manage their condition better, the present research could not replicate these findings using data from the ELSA.

# Chapter 3

# Preference heterogeneity and long-term outcomes of people living with type 2 diabetes (T2DM): findings from the experimental risk module of the English Longitudinal Study of Ageing (ELSA)

## 3.1 Introduction

While an extensive stream of literature links the 'classic' type 2 diabetes risk factors such as age, BMI, or ethnicity to health (and cost) outcomes, few studies investigated whether and to what extent heterogeneity in individuals' time and risk preference rates might impact upon these outcomes. Therefore, the present analysis will explore further the relationship between preferences and adherence by simulating the long-term outcomes of people living with T2DM according to the level of their time and risk preferences. This goal will be achieved using the United Kingdom Prospective Diabetes Study Outcome Model 2 (UKPDS-OM2), a disease progression model which permits accurate simulations of key health outcomes of people living with T2DM. A wide range of individual-level socio-demographic and health-related information will be utilised to populate the UKDPS-OM2, where participants will be stratified according to the level of their preferences. In doing so, this study will uncover the opportunity to quantify the long-term impact of preferences upon the management of T2DM, representing a novel contribution of the current analysis to previous literature. To my knowledge, there is no existing work that has calculated lifetime predictions of people with T2DM, linking survey data to a detailed disease progression model such as the UKPDS.

The whole chapter is divided into five main sections. The first section provides a qualitative appraisal of the existing models in type 2 diabetes and motivates the choice underlying the selection of the UKPDS-OM2. It will also contain a brief literature review on the link between time preference and mortality as well as a general discussion on preference heterogeneity in cost effectiveness analysis. The second section about the methods outlines a detailed classification of the UKPDS-OM2 input-output requirements and the main model structure. The third

section contains a description of the ELSA cohort, information on how the sample was constructed, and the strategy used to deal with missing data. Finally, the fourth and fifth sections will report the results and discussion respectively.

### 3.1.1 A review of the existing models in type 2 diabetes

Several economic models in T2DM have been developed over the past two decades [94] [95] [96]. These models share a similar general structure and main assumptions [95]. However, they differ in input requirements, outcomes, complications, data sources, uncertainty, and validation procedures. The current section describes the main differences and similarities among these models to detail the reasons for the final choice of the UKPDS-OM2. Based on the previous literature on the topic and the guidelines for decision analytical modelling in the Health Technology Assessment suggested by Philips and et al., 2006 [97], I constructed a set of criteria to guide the final decision [95, 97-99]. More precisely, I compared the existing models in type 2 diabetes against the following seven criteria:

1) The model must be able to accommodate patient-level data.
2) Diabetes specific requirements: the model time-horizon should adequately capture the long-term nature of type 2 diabetes. The model structure must capture the multidimensionality of type 2 diabetes, including both macro-vascular and micro-vascular complications. Nonetheless, they must permit potential interdependence between these complications.
3) Validation, since the model should be both externally and internally validated.
4) Uncertainty should be addressed through sensitivity analysis and Monte Carlo simulations.

5) Transparency in reporting the technical component of the model such as an explicit model diagram, equations, transition probabilities and data sources.
6) The frequency of application in HTA submissions.
7) Model availability: for example, whether the model was free to use, available under free or paid licence.

At present, NICE has not released modelling guidelines specific to diabetes [100]. Therefore, I adopted the criteria mentioned above from previous systematic reviews and the guidelines for modelling T2DM and its complication published by the American Diabetes Association [101]. The only exception is criterion number one, which is partly a direct consequence of the structure of the ELSA dataset and partly stems from the research question this research is addressing. The ELSA dataset contains micro-level data; therefore, a model that accommodates patient-level information is more appropriate to exploit the dataset at its full potential. Furthermore, micro-level models have the advantage of better capturing the inter-independence among different complications that may arise from T2DM [96]. Consequently, a microsimulation model is a more suitable choice over other tools that could only accommodate aggregated data.

After a pragmatic literature review of existing economic models in type 2 diabetes, a total of 29 models were identified. Then, using a hierarchical exclusion principle, all these models were evaluated against the selection criteria. For example, suppose a model did not satisfy the first criterion. Then, the same model was excluded from the list of potential candidates and thus not evaluated against the following criterion, which is represented by criterion number two in this example.

The models for type 2 diabetes identified in this qualitative assessment are reported in figure 3.1, alongside their description and the critical information such

as main model structure, primary data sources and list of complications included. Among these models, ten are Markov-based cohort models, thus not accommodating our patient-level dataset. Three models employed a Markov approach, but it was unclear whether these used cohort or patient-level analysis and were excluded. An additional model didn't report its modelling technique and was also excluded. Amongst the remaining models, seven are micro-simulation Markov, five discrete-time microsimulations, one made use of a differential equation, one employed a decision tree approach, and the remaining one was a combination of decision tree and Markov techniques. Amongst the eleven models able to accommodate patient-level data, all of them were equally able to satisfy the diabetes-specific requirements apart from Eastman and GDM, which were lacking in accounting for the interdependence between complications [102]. The ADA specific guidelines about diabetes modelling highlight the importance of including a tracker variable or a similar method to account for the interdependence between complications; thus, the models above (Eastman and GDM) were excluded. Most of the models adopted a lifetime time-horizon suitable for a long-life chronic disease such as type 2 diabetes or a simulation period sufficient to capture all the possible relevant consequences of this condition [95]. None of the models' time horizons is shorter than forty years.

Given that the sample's mean age is almost sixty years, all the models have an adequate time horizon for the scope of this research [95]. Furthermore, all the models include the main relevant complications and are almost equally able to capture the multidimensionality of type 2 diabetes. The most common macro-vascular complications in these models are coronary heart disease, myocardial infarction, stroke and cerebrovascular disease [99]. Retinopathy (eye damage),

nephropathy (kidney damage), neuropathy (nerve damage) and amputation are the most common among microvascular complications [99].

The models share similar sources of data. For example, the United Kingdom Prospective Diabetes Study (UKPDS) and The Diabetes Control and Complications Trial (CDC) are the most common trials used to build and populate the models [95, 102]. The Framingham cardiovascular risk-equations are the most shared data source for cardiovascular risks. At the same time, The Wisconsin Epidemiologic Study of Diabetic Retinopathy (WESDR) is the recurrent source of information for cumulative rates of incidence of macular oedema (ED) [95, 102].

In terms of input-output requirements, several models could be appropriate for the present analysis. The ELSA dataset contains many demographics and biomarker information that can potentially satisfy the requirements of numerous simulations tools [34]. Furthermore, all the models provide outcomes compatible with the current research question, such as life expectancy, QALYs, or equally valid durations and quality of life measurements. All the models up to this point also included healthcare costs coherent with the present research question [95, 99, 100].

As emphasised during the Fifth Mount Hood Challenge [98], the ADA guidelines [102] and the ISPOR task force [103], transparency is crucial in reporting a model. According to this view, each models' original publication or companion paper should report in sufficient detail all the relevant information needed to reproduce the model and its result. The Cardiff diabetes model reported a detailed model diagram but did not provide sufficient detail to determine events and transitions; Eagle and Caro et al. did not provide a diagram in their paper [102]. Archimedes is a highly complex system of differential equations, making it hardly accessible

to a non-technical audience. All these three models were excluded from the next stage of this qualitative assessment for the reasons outlined above.

Transparency does not imply accuracy, so I used a further criterion to assess model validation. That is, a model is useful when it can make relevant predictions. On the one hand, internal validation refers to the model's capability to reproduce the trial results or any other data source used to populate the model [100]. On the other hand, external validation refers to its ability to predict results in data not used to build the model. In this sense, only seven of the remaining models were both externally and internally validated. On the contrary, Syreon was only internally validated, whereas the Diabetes Model was only validated with external data.

The quality of a model is not assessed exclusively on its capacity to generate accurate estimates but also on its ability to reproduce the uncertainty surrounding these estimates accurately [95]. This kind of uncertainty can be reduced using a sufficiently large number of Monte-Carlo replications. Concerning this specific criterion, all models included, up to this stage, have addressed uncertainty to some extent. The way they addressed uncertainty around the predicted point estimates was achieved either via univariate deterministic (DSA) or probabilistic (PSA) sensitivity analysis or both. The former refers to a method employed to test the sensitivity of the model’s results to variations in a specific input parameter or set of parameters. According to the DSA method, one or more input parameters are manually changed, usually around a range of prespecified values. The results are then analysed to determine how sensitive the output values are to these changes in the input values. Instead, in PSA, all the parameters' values, previously drawn from a priori defined probability distribution often using Monte Carlo simulations, are changed simultaneously. DSA and PSA are both

recommended by the guidelines released by the ISPOR task force to explore uncertainties around the model's inputs. However, not all the models address second-order uncertainty appropriately via probabilistic sensitivity analysis. While first-order or stochastic uncertainty relates to the random variability in outcomes between identical patients, second-order uncertainty refers to the probability that governs outcomes are themselves uncertain [95, 99, 102]. The parameters must be estimated and thus affected by some degree of uncertainty around their actual value. The description of the Michigan models was not sufficiently clear in describing the methods used to deal with uncertainty and was excluded.

Besides assessing models' technical components, evaluating their applicability and credibility is crucial. In this sense, I adopted the frequency of application in HTA submissions and relevant literature to measure the credibility and applicability of the model. With this regard, The Core and The UKPDS are respectively the first and the second most common models in terms of HTA reimbursements, conference proceedings and literature citations. However, even though ECHO, Sheffield and Jade were hitherto equally able to satisfy all the criteria, they have been used less frequently when compared to the CORE and UKPDS. For this reason, they were not assessed against the last criteria of availability.

Based on this qualitative assessment, ultimately, two models were equally able to satisfy all the criteria described above: the CORE and the UKPDS. Given that both could potentially fulfil the purpose of this research question, the final decision was based exclusively on their accessibility. The CORE is available only under paid commercial licences, whereas the UKPDS is available under a free licence for research purposes. Therefore, the final choice was the UKPDS. In addition, NICE has already made extensive use of the model in both clinical guidelines and

technology appraisals. Although this aspect further pointed out the UKPDS as the final choice, it has not been directly included in the list of criteria. Since this research employs data from a representative sample of the English population, I thought adopting a model developed and validated in the UK would be the better choice.

Nevertheless, it is essential to clarify that this qualitative assessment aimed to identify a model to satisfy the current research question. This does not mean the excluded models are less valid than the UKDPS-OM2; as many authors have pointed out, there is no reference case for type 2 diabetes modelling [95, 100, 102]. Furthermore, even if this review has identified many economic models in T2DM, a systematic approach was not adopted. Consequently, it is essential to acknowledge that other equally valid models not included in this assessment may exist which have not been included in the present review.

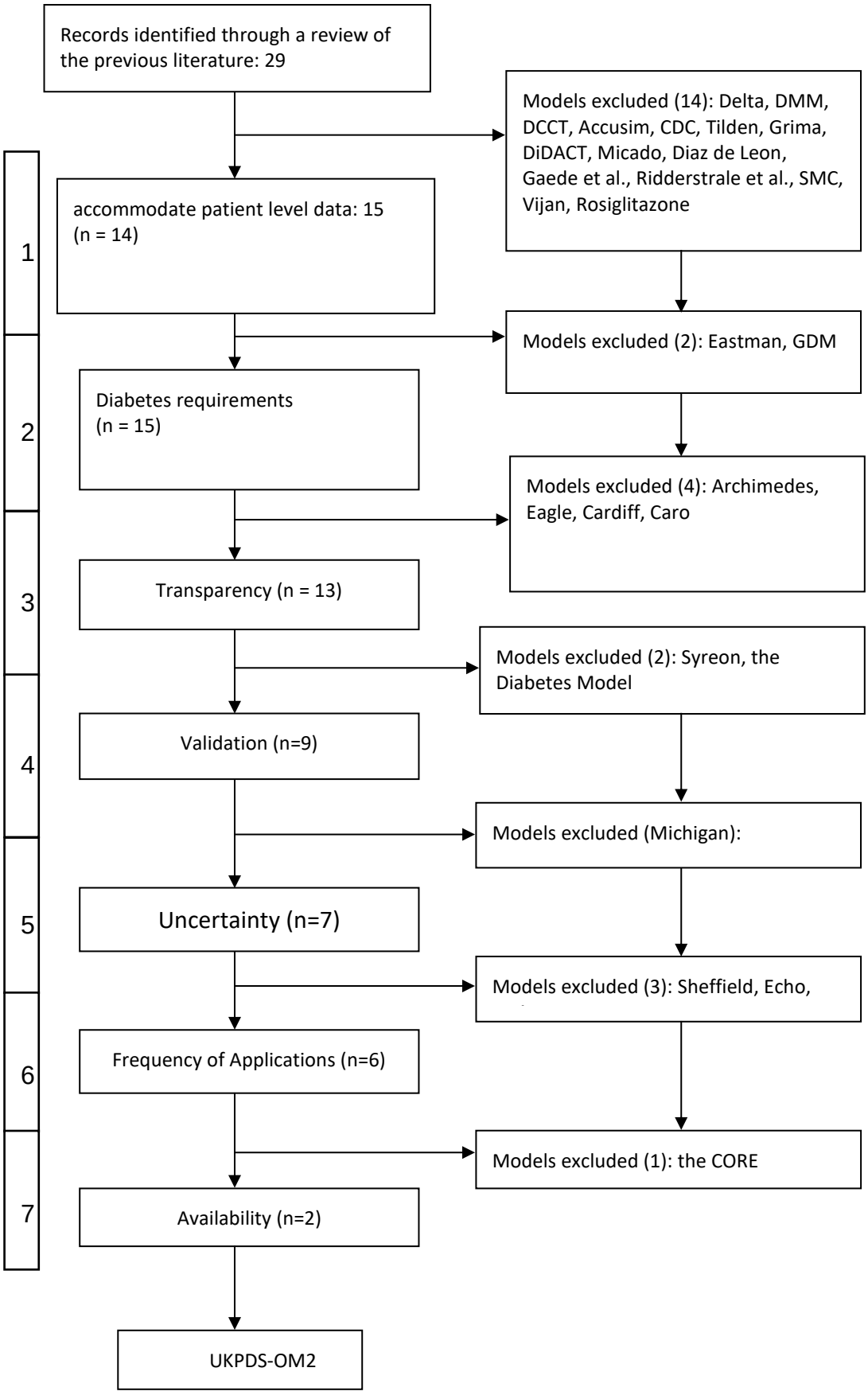


**Figure 3-1 Flowchart diagram of the model selection**

| Model | Description | Outcomes | Model type | Monte Carlo | Complications | Data | Validation |
|---|---|---|---|---|---|---|---|
| MICHIGAN (THE US, 2005) | Discrete state, discrete-time, a semi-Markov tool with Monte Carlo techniques to model the disease progression. The cycle lasts one year, and five health states represent the development of glucose tolerance (standard glucose tolerance, impaired fasting glucose, impaired glucose tolerance and type 2 diabetes). Among the complications, the model accounts for retinopathy, nephropathy, and neuropathy, while stroke and coronary heart disease are the significant comorbidities. A set of baseline characteristics and the actual health state and treatment option determine the initial health state. Subsequently, a random number between 0 and 1 is drawn from a uniform distribution and compared to a transition | Health-utilities and costs. The user can specify the length of the simulation period years and the compliance rate with the treatment and medications. | Discrete-time microsimulation | Yes | Both Microvascular (retinopathy, nephropathy, and peripheral neuropathy) and Macrovascular (stroke and CHD amputation, blindness in one eye | WEDSR, UKPDS | Internal, External |

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| | probability. If the random number is equal to or less than the transition probability, the individuals move from their current health states towards the following health states. Once the transition occurs, it's irreversible. It uses the health-utilities score from the Quality of Well Being-self-administered, whereas costs were retrieved from medical claims. The model has been successfully validated using 4 and 10 years of follow-up data from the Wisconsin Epidemiological Study of Diabetic retinopathy (WEDSR). | | | | | | |
| ECHO-T2DM (Sweden ,2013) | Independent Markov health states embody the progression of micro and macro-vascular complications. Users can define the time-horizon of the simulation period, and patients may be assigned either to a treatment or control group. During each cycle, which lasts one year, patients are stochastically assigned to different micro and macro-vascular health states, according to their baseline characteristics and history of pre- | QALYs, Life-expectancy, mean survival, direct costs for each event. Outputs are then combined to calculate incremental cost-effectiveness ratios (ICERs) | Micro-Markov | Yes | Microvascular (retinopathy, nephropathy, neuropathy) Macrovascular (IHD, MI, CHF, Stroke), mortality | UKPDS, DiDACT | Internal, External |

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| | existing events. Users can specify their preferred treatment sequence, and new medication can be added or discontinued throughout the simulation period. Transition probabilities were acquired from the DIDACT study and UKPDS risk equations. It has been validated according to the criteria suggested by the International Society for Pharmacoeconomics and Outcomes Research (Ispor). | and Net Monetary Benefits (NMBs). | | | | | |
| CORE (Swizterland,2004) | A sequence of fifteen Markov sub-models, one for each complication, simulates the progression of the patients across the different health states. The complications are the following: cardiovascular disease, eye disease, hypoglycemia, nephropathy, neuropathy, foot ulcer, amputation, stroke, ketoacidosis, lactic acidosis and mortality. It employs Monte-Carlo simulation with tracker variables which permit the interconnection between all the different sub-models and avoid the memory-less limitations of the Markov model approach. Therefore, patients can experience more | Cumulative event rates/incidences; Annual costs per patient; Cumulative costs per patient; Breakdown of costs per complications/ treatment; Life expectancy; Quality-adjusted life expectancy; Incremental | Micro-Markov | Yes | retinopathy, nephropathy, neuropathy, foot ulcer, macular oedema, cataract, hypo, ketoacidosis, lactic acidosis, MI, angina (2 states), CHF, stroke, PVD, mortality | Framingham cardiovascular risk-equation, UKPDS, DCCT, WESDR, EURODIAB | Internal/External |

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| | than one complication within a specific cycle. The cycle length is fixed throughout the analysis period and equals one year. The baseline characteristics the model account for are Age, Gender, Duration of diabetes, Racial characteristics, Baseline HbA1c, Blood pressure BMI, Lipid levels Smoking, Baseline complications. The user can modify costs and clinical data. | cost-effectiveness ratios; Sensitivity analysis; Budget impact analysis. | | | | | |
| UKPDS-OM2 (the UK, 2013) | The stochastic, discrete-time, Markov model uses Monte Carlo techniques to predict the occurrence of diabetes complications. In total, seven diabetes-related complications are possible (MI, angina, strokes, heart failure, amputation, renal failure, and blindness) plus an additional equation for all causes of mortality. The likelihood for a patient to experience one or more of the above endpoints depend on its demographic characteristics (age, gender ethnicity), modifiable and non-modifiable risk factors for diabetes (haba1c lipid profile blood-pressure white blood-cells haemoglobin glomerular filtration rate haemoglobin weight height | Quality-adjusted life expectancy, life expectancy and costs. Otherwise, update the history of the diabetes-related event, and the cycle starts again. | Discrete-time microsimulation | Yes | MI, IHD, stroke, congestive heart failure, amputation, renal failure, blindness in 1 eye, all-cause of complications | UKPDS | Internal/external |

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| | duration of diabetes), history of pre-existing complications and management strategies. Patients can be assigned up to three different groups. The maximum simulation period is 70 years. | | | | | | |
| CARDIFF (the UK, 2006) | A discrete-event stochastic simulation tool with a time – horizon of up to 70 years. It shares its fundamental structure with the seminal model Eastman DCCT, but the cardiovascular equations have been updated with the UKPDS risk engine. We can find the baseline cohort characteristics: age, gender, smoking status, glycated haemoglobin, high-density lipoprotein cholesterol, systolic blood pressure total cholesterol. The list of complications comprises: MI Stroke CV death, Retinopathy Nephropathy Neuropathy Non-CV death. It has been validated against the UKPDS and Eastman model, while The EuroQuol (EQ-5D) was used to measure health-related utilities. | QALYs, Total cost and the aggregate number of a clinical event. | Micro-Markov | Yes | MI, stroke, CHD, ESRD, VL, amputation | UKPDS | Internal/External |
| ARCHIMEDES (US 2003) | A continuous model that uses differential equations to replicate the pathophysiology of diabetes. The high-level clinical details of the microsimulation tool are | It covers a broad range of outcomes, among which we can find: | An interrelated system of differential equation | No | Simulates patients' anatomy and physiology | DCCT, UKPDS | Internal/External |

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| | guaranteed by more than 50 interconnected biological continuous variables. It has been validated against eight-teen different clinical trials. | clinical (e.g. glucose metabolism), financial (costs of therapies, admissions) logistics. | | | | | |
| SHEFFIELD (THE UK, 2013) | The model is at the patient level and replicates patients' risk of progression through five comorbidities: retinopathy, nephropathy, neuropathy, coronary heart disease, and cerebrovascular disease. The intensity of management and monitoring can be varied by altering targets such as those for glycemic control, the requirement for insulin, blood pressure control, and the intensity of lipid-lowering therapy. The model is primarily based on the Eastman models for microvascular complications, using the Diabetes Control and Complications Trial (DCCT). In addition, the model uses equations from the United Kingdom Prospective Diabetes Study (UKPDS) for macro-vascular complications. | Total costs are obtained by adding the costs of therapy, one-off treatments (for example, cost of amputation), and ongoing treatment of complications (for example, treatment following stroke). The health benefit, the incremental quality-adjusted life years, is obtained by | Micro-Markov | Yes | retinopathy, nephropathy, neuropathy, coronary heart disease, and cerebrovascular disease | DCCT, UKPDS, WESDR, Eastman, EDIC | Internal/External |

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| | | applying quality of life measures to the time spent in the various diabetic health states. | | | | | |
| EAGLE (2006, France, Germany, Spain, US, The UK) | Object-oriented probabilistic Monte Carlo simulation application. A Markov process with yearly intervals is the basic structure of the model. Transition probabilities depend on the simulated patient's status, with related calculations defined internally. Among various demographics (e.g., age, duration of diabetes, and sex), physiologic characteristics (e.g., A1C and systolic blood pressure), preexisting complications, and lifestyle input parameters (e.g., smoking), the primary determinant of events are A1C, which is simulated over time concerning predefined target A1C. Twenty outcomes (e.g., hypoglycemia, retinopathy, macular oedema, end-stage renal disease, neuropathy, diabetic foot syndrome, MI, and stroke) are projected based on | Provide output data on costs (of treatment and complications), cost-consequence, quality of life, and cost-effectiveness of interventions | Discrete-time microsimulation | Yes | Retinopathy, nephropathy, neuropathy, hypoglycemia, MI, angina pectoris heart failure, MI, stroke, mortality | DCCT, UKPDS, WESDR | Internal/external |

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| | epidemiological and clinical trials, including the UKPDS. In addition, it can simulate the progression of type 1 and type 2 diabetes. | | | | | | |
| JADE (2008, US) | Probabilistic discrete event Monte Carlo microsimulation model where a complex treatment algorithm ( up to six treatment regimens over patient's lifetime) in addition to the UKPS Outcomes model risk equations and algorithms. It can evaluate treatment sequences containing up to six treatments and include adverse events. It has been internally and externally validated and is available under license. | Costs effectiveness of the intervention | Discrete-time microsimulation | Yes | stroke, heart failure, renal failure, amputation, blindness, mortality | UKPDS | Internal/external (even if partially reported) |
| DiDACT (2001 UK) | A compact sequence of Markov chain modules describes patient probabilities of experiencing diabetes complications. These sub-models are arranged into a Metabolic model, and an economic Model linked together. | Longevity, health-care costs | Markov-cohort model | No | Retinopathy, nephropathy, neuropathy | DCCT, UKPDS | not clear |
| Grima (2007, Canada) | A long-term, state-transition model simulates the natural history of type 1 and 2 diabetes. Risks of diabetes-related macro- and microvascular complications and mortality are estimated using | Life years, QALYs, healthcare costs | Markov-cohort model | No | amputation, retinopathy, MI, HF, stroke | UKPDS | Internal/external (external not very well reported) |

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|---|---|---|---|---|---|---|---|
| | the UKPDS. The time horizon is 36 years. | | | | | | |
| Tilden (2007, UK) | A decision-analytic model was employed as a first-order Monte Carlo simulation of a Markov process. The clinical variables used in the model relate to the HbA1c and the lipid and body mass index (BMI) profile of the cohort as they progress through the lifetime model. In addition, utility values were derived using the EQ-5D. | QALYs, health care costs | Markov-cohort model | Yes | ischemic heart disease (IHD), blindness in one eye, congestive heart failure, MI, stroke amputation, renal failure, death | UKPDS | Not reported |
| CDC (2002, US) | A semi-Markov Monte Carlo simulation model. The model simulates the development and progression of the major complications of the disease under each assigned alternative. | life-years, QALYs | Markov-cohort model | No | angina; cardiac arrest, MI; history of cardiac arrest/MI; stroke, nephropathy; low microalbuminuria/high macro albuminuria; nephropathy, death | UKPDS, CHANGES III | Internal/External |

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| Eastman (1997, US) | Each year of life is simulated until death occurs after the person's age, race, and sex status are assigned. Fourteen health states are modelled, reflecting the natural history of the vascular and neuropathic complications of diabetes | Predictions of complications and mortality | Micro-Markov | Yes | retinopathy, nephropathy, neuropathy, CVD morbidity, and mortality | Framingham risk-equations, clinical trials | Internal not clear/ external missing |
| GDM (2000 UK, US) | Continuous, stochastic, Monte Carlo Microsimulation model. It has been constructed using a continuous prediction equation. | Predicts medical futures of both individuals and populations with diabetes | Discrete time microsimulation | Yes | retinopathy, nephropathy, neuropathy, 12 major-diabetes related CVD events and secondary events, mortality | Framingham, Kaiser Permute Northwest, UKPDS, NHANES III, US Renal data System | Neither internal nor external |
| DCCT (1996, US) | Probability model, based on extrapolation from experience with type 1 diabetes, to evaluate the efficacy of glycemic control in type 2 diabetes | Risks for developing blindness and end-stage renal disease; several patients and patient-years needed to treat to prevent complications. | Markov-cohort model | No | retinopathy, nephropathy, , and mortality | Rochester and WESDR. UKPDS | Neither internal nor external |

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|---|---|---|---|---|---|---|---|
| DMM (2007, Switzerland) | A cost model and a utility model linked together allow calculating the cumulative incidences of cost and QALYs. The time horizon is fixed to ten years | cost and QALYs | Markov model but not clear whether cohort model or microsimulation | No | retinopathy, nephropathy, , and mortality | A cohort of patients in Switzerland without long term complications | Internal/external |
| Delta (Hungary? 2007) | The health economic model projects outcomes for selected patient populations, considering baseline patient characteristics, history of complications, changes in physiological parameters over time, diabetes treatment and management strategies | Life-expectancy, costs | Markov model but not clear whether cohort model or microsimulation | No | (Ischemic heart disease, retinopathy, hypoglycemia , nephropathy, neuropathy, foot ulcer, peripheral vascular disease, stroke and ketoacidosis) | Not clear | Neither internal nor external |
| Syreon (Hungary?) | The health economic model projects outcomes for selected patient populations, considering baseline patient characteristics, history of complications, changes in physiological parameters over time, diabetes treatment and management strategies, and screening programs | Patient-level outcomes but not clear what they are | Combination of Decision tree and micro-Markov technique | Not reported | stroke, IHD, MO, nephropathy, PVD, hypoglycemia | Not clear | Internal |

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|---|---|---|---|---|---|---|---|
| Diaz de Leon Castaneda (Mexico, 2012) | Markov model was designed to simulate the economic and health outcomes of different treatments with Oral Hypoglycemics Agent | cost and QALYs | Markov-cohort model | yes | Not reported | New risk equations were calculated based on a systematic review and meta-analysis conducted by the authors | Not reported |
| The Diabetes Model (Australia, 2011) | Diabetes Model designed to calculate the long term benefits of public health strategies | potential costs and benefits of a given intervention | Micro-Markov | Not reported | MI, stroke, CHF, angina, cerebrovascular disease | Australian National Diabetes Information Audit and Benchmarking (ANDIAB) initiative / The Australian Diabetes Obesity and Lifestyle Study (1999-2000) | External |
| Gaede et al., 2008 (Denmark, 2008) | A two-state Markov model (alive and dead) with a cycle length of 1 year was | cost and QALYs | Markov-cohort model | Not reported | MI, stroke, CABG, PCI, HF, ESRD, amputation | UKPDS | Not reported |
| Ridderstrale et al., 2011 (Sweden, 2011) | A short-term (one year) cost-effectiveness model developed in Microsoft Excel® 2003 | cost and QALYs | Not reported | Not reported | Not reported | Not reported | Not reported |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SMC (2009) | A report comparing two different dosages of metformin | long-term outcomes associated with diabetes | Decision tree | no | Included but not apparent what they are | Not reported | Not reported |
| Caro (US 2000) | Model built ad-hoc to assess the benefits and costs of troglitazone to improve glycaemic control | long-term outcomes associated with diabetes | Micro-Markov | | retinopathy, nephropathy, neuropathy, hypoglycaemia, macrovascular disease, and mortality | UKPDS, DCCT, Rochester, Wisconsin data, Framingham risk | Internal? |
| Mikado (Netherlands, 2015) | A Markov-type, multistate transition model with a 1-year cycle length | include incidence and prevalence of complications, quality of life, costs | Markov-cohort model | no | retinopathy, nephropathy, mortality, diabetic foot | Dutch national registries and systematic literature reviews | Internal/ partly external |
| Vijan, (US, 1997) | Mode designed to evaluate the benefits of intensive glycemic control in patients with type 2 diabetes | Risks for developing blindness and end-stage renal disease; | Markov-cohort model | no | retinopathy, nephropathy, and death | DCCT, Rochester and WESDR | Internal/ external |
| Rosiglitazone (NICE, 2000) | Model built to evaluate the clinical efficacy of Rosiglitazone | pharmacology, pharmacokinetics, clinical efficacy, adverse effects, drug interactions, | Markov cohort? | | CHD, stroke, neuropathy, nephropathy, VL | UKPDS and Framingham risk equations | External |

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| | | and dosing of rosiglitazone, | | | | | |

**Table 3-1-description of the primary model in predicting the long-term outcomes of Type 2 Diabetes included in this assessment.**

### 3.1.2 Literature review on the link between time preferences and mortality

A brief narrative literature review was conducted to investigate the link between time preferences and mortality. Research from Daly et al., 2018 [104] examined the relationship between time perspective and all causes of mortality over a nine-year follow-up period exploiting data from the ELSA. They measured time preferences using an item contained in the ELSA wave 1 “Expectation” module, which asked participants about the length of their financial planning horizon. Responses were measured on a six-points scale ranging from *day to day or less* (coded as 1) to *longer than ten years* (coded as 6). The authors employed Cox proportional hazards regression models, which were adjusted for a wide range of baseline covariates, i.e., age, sex, childhood socioeconomic status, education, wealth, financial difficulties, and chronic illnesses. Estimates from these models showed that panning for more extended periods of time (10 years or more) was associated with a decrease of 32% in the risk of death (HR = 0.68, 95% CI: [0.51, 0.91], $p < .01$). However. Controlling for health behaviour (smoking, alcohol consumption and physical activity) attenuated this association by 32% once the relative contribution of smoking and alcohol to the probability of dying over the nine-year follow-up period was decomposed. This decomposition analysis uncovered a statistically significant indirect effect of both physical activity ($p<0.01$) and smoking ($p<0.01$) which explained the 21% and 13% respectively of the relationship between time preference and all causes of mortality.

A recent study conducted by Norrgren [105] in 2022 examined the role of time preference as a potential predictor for illness and premature mortality, i.e., before the age of 65. A cohort of 12,956 individuals born in Sweden in 1953 was asked at the age of 12/13 in 1966 whether they preferred SEK 100(~US$19.3)

immediately or SEK 1000 in five years, which enabled the author of the study to construct a binary indicator for participants time preferences. This variable was coded as one if the adolescent opted for the delayed reward and 0 otherwise. Subsequently, participants were followed with registry data until 2018 to ascertain the predictive power of time preferences upon the probability of dying prematurely and to experiencing ill health. Results from Cox hazards regression models controlling for a wide range of sociodemographic variables (month of birth, sex, age at their child's birth, fathers' and mothers' total income, and information on university and upper secondary schooling for the parent with the highest level of education parents' age) showed that the more patient children, i.e., the low discount rate category had 21% lower chances of dying prematurely at any given time point between the age of 40 and 65 years old. Once cognitive health and cognitive controls were added to the models, the effect of time preferences persisted and confirmed that the more patient adolescent had a 17% lower mortality risk. Regarding the impact of time preference on the likelihood of experiencing illnesses in later life, results from OLS linear models with the total number of either hospitalisations or diagnosis in the participants adult's life uncovered that adolescent who choose the delayed reward had 0.6 fewer hospitalization and 1.5. fewer diagnoses in adult life. All these results were robust to several different econometric specifications, i.e., Poisson models instead of OLS for the analysis about illnesses and robustness checks such employing restricted/unrestricted samples and different sets of covariates.

One study by Thirumurthy et al., 2015 [106] investigated the extent to which time preferences predicted mortality and adherence to treatment among a group of patients receiving antiretroviral medication therapy (ART) for HIV in Kenia. A total of 220 participants to the ART programme had their time preferences measured

at enrolment. Preferences were elicited within RCT setting through a hypothetical monetary payment where participants were asked to choose whether they would rather receive 550 Kenya Shillings (about US$7.00) immediately or 1,000 Kenya Shilling (US$12.50) in one year time. Based on the response to this task, individuals who opted for the delayed option were classified as having a low discount rate, i.e., more patient, and individuals who chose the more immediate hypothetical pay-off as having a high discount rate, i.e., more impatient. Binary logistic regression models showed that participants with high discount rates had significantly higher probability of mortality at 48 eight-week follow-up than participants with low discount rate (9.3% vs. 3.1%). This association was confirmed by an additional analysis where the model was adjusted for various covariates (age, sex, education marital status, household size, travel time to clinic, wealth, alcohol use, whether the participants felt tired over the past week as a measure of health status) odds ratio 3.84 (95% CI 1.03, 14.50). However, as measured by Medication Event Monitory System (MEMS), adherence to ART therapy was comparable between the two groups of participants with high and low discount rates, respectively (42.3% vs. 49.6%, AOR 0.70; 95% CI 0.40, 1.25).

In summary, the study included in this review suggests that time preferences impact mortality, and more generally behaviour such as adherence that can be related to adverse health outcomes. Furthermore, it must be noted, that all the empirical studies included in this brief literature utilise econometric techniques to gauge the direct effect of time preference on mortality. While this approach undoubtedly has several advantages over using a decision analytical model, such as greater flexibility in terms of methodologies and the ability to control for a wide range of covariates both at individual and household levels which can be particularly important in certain context where intra-household dynamics can play

a role, I decided to opt for a more indirect approach in the form of a decision model for three main reasons. Firstly, simulation models such as the UKPDS are valuable tools to extrapolate the progression of health and cost outcomes for longer periods compared to RCTs or survey data in most cases. A notable exception is represented by the study of Thirumurthy et al., 2015 [106] which had a considerably more extended follow-up compared to the other research mentioned above [104, 105]. However, even in this case, the analysis did not benefit from a lifetime horizon as the UKPDS allows. Secondly, preliminary data analysis from our sample showed that the two groups of high and low time preference did not differ significantly regarding baseline characteristics, as seen in Table 3.5 where any tests yield statistically significant result. The fact that the two groups did not differ provide a reasonable degree of reassurance that the output we might observe from the model are not driven by differences in baseline values between the two groups but rather are more likely to reflect genuine differences in how participants trade off current and future benefits. Finally, the present study aimed to calculate whether time and risk preferences could represent a potential way to make interventions in T2DM more effective and cost-effective. In decision analytical models' outcomes are often quantified in terms of costs and QALY. Therefore, they are more suitable for this research than other approaches, which use sources of data where this information is not typically collected. Therefore, for all these reasons outlined above, the decision to adopt a simulation modelling approach.

### 3.1.3 Preference heterogeneity in cost effectiveness analysis

The sustainability of publicly funded healthcare systems is experiencing increasing pressure worldwide. Cost-effectiveness analysis aims to maximise population health given an exogenously determined budget constraint [107].

However, decisions on treatment allocation based on average measures of cost-effectiveness may lead to suboptimal usage of scarce resources. The treatment effect of an intervention, medical device, or drug will differ across the population who are recipients of that treatment or intervention [108]. An intervention for one type of patient may not be cost-effective, at least to the same extent for other types of patients. In other words, the same intervention may produce heterogeneous outcomes for different population subgroups due to differences in sociodemographic characteristics, biological factors, and patient preferences. Not incorporating this heterogeneity in cost-effectiveness analysis may represent a unique missed opportunity to improve population health. It is not surprising that many national healthcare agencies recommend analysing subgroups before adopting a new technology. In the most recent manual on health technology assessment, the NICE recommends: “For many technologies, the level of benefit will differ for patients with differing characteristics. In cost-utility analyses, explore this as part of the analysis by providing clinical- and cost-effectiveness estimates separately for each group of patients” [109]. As mentioned in Chapter 2, heterogeneity in time and risk preferences may contribute to explaining differences in how people living with diabetes can adhere to the guidelines for managing T2DM, and consequently, their long-term health outcomes. By providing additional information on this relationship, the present analysis may offer valuable insights on how to make policy interventions in T2DM more cost-effective.

## 3.2 Methods

Participants characteristics at baseline by time and risk preferences group will be compared using t-tests and chi-squared tests. Long terms outcomes i.e., costs

and QALE will be calculated using the UKPDS-OM2.The following section will provide a detailed description of the UKPDS inputs-outputs requirements.

### 3.2.1 Description of the United Kingdom Prospective Diabetes Study Outcome Model 2 (UKPDS-OM2)

#### 3.2.1.1 Inputs

Table 3.2 describes the set of inputs required by the UKPDS-OM2.

| **Demographic Characteristics** | **Description** | **Contained in the ELSA (yes/no)** |
|---|---|---|
| Individual Identifier | Unique Individual Numeric identifier | Yes |
| Ethnicity | White/Non-white | Yes |
| Gender | Male/Female | Yes |
| Age | Age expressed in years / continuous | Yes |
| Duration of diabetes | Duration of diabetes expressed in years | Yes |
| Weight | Current weight expressed in Kg | Yes |
| Current smokers | Whether the participants smoke yes or no | Yes |
| **Risks-factors** | | |
| High-density lipoprotein (HDL) (mmol/mol) | sometimes referred to as "good cholesterol", its function is to transport fat molecules out of artery walls back to the liver | Yes |
| Low-density lipoprotein (LDL) (mmol/mol) | sometimes referred to as "bad cholesterol", is one of the five major groups of lipoproteins that transport all fat molecules around the body in the extracellular water | Yes |
| Systolic blood pressure | Systolic Blood-Pressure (bpm) | Yes |
| Glycated haemoglobin (HbA1c) (%) | Average blood glucose (sugar) levels for the last three months. | Yes |
| Weight (Kg) | Weight expressed in Kgs | Yes |
| Heart rate | Beats per minute | Yes |
| White blood cell count (WBC) | a test that measures the number of white blood cells in the body | Yes |
| Haemoglobin | a red protein responsible for transporting oxygen in the bloodstream | Yes |
| Estimated glomerular filtration rate (eGFR) | a measure of renal function | No (estimated through a specific formula) |

**Table 3-2 UKPDS-OM2 model inputs (UKPDS)**

#### 3.2.1.1.1 Inputs - demographic characteristics

The demographic characteristics (age, gender; ethnicity; duration of diabetes; smoking status) were retrieved from the ELSA main questionnaire. The only exception was the variable weight taken from the ELSA nurse module. The weight of the ELSA participants was measured in Kilograms by a registered nurse at the respondents' home, and it was estimated for those who either couldn't stand up or weighed more than 130 Kilograms. There were no variables that recorded the exact duration of diabetes. A variable that reported the wave at which the diagnosis of diabetes or high blood sugar reading firstly occurred was available. Thus, I could retrieve a proxy measure for the duration of diabetes by subtracting from the year at which wave six took place (2012) the year corresponding to the wave at which the diagnosis of diabetes was firstly reported. For instance, in this case, the duration of diabetes was equal to 4 years. Even if this procedure is likely to underestimate diabetes duration, i.e., people diagnosed in between waves have their diagnosis only reported at the subsequent wave, this was the only feasible procedure to obtain information about the duration of diabetes. This might have a significant impact on the following analysis, in the sense that the outputs of the model might be downward biased given the way durations of diabetes had been constructed. The indicator for smoking status was derived from an item located in the ELSA main questionnaire, which asked the respondents whether they were smoking at all at the time of the interview. Given the self-reported nature of this variable, the percentage of smokers among our sample is also likely to be underreported. It is well documented in the literature that current smokers often underreport their smoking status [110]. The fact that smoking status is with all probability underreported is also likely to impact the present analysis, i.e., model estimates will be more conservative.

#### 3.2.1.1.2 Inputs – biomarkers

As highlighted in table 3.2, The UKDPS-OM2 requires several T2DM related risk factors for the model before running the simulation. These risk factors include high-density lipoprotein (HDL), low-density lipoprotein (LDL), systolic blood pressure (BP), glycated haemoglobin (HbA1c), white blood-cells count (WBC), haemoglobin and estimated glomerular filtration rate (eGFR). Cholesterol is a fat-like waxy substance found in all human body cells [111]. The liver produces it, but it can also be found in certain foods such as dairy products, egg yolks, and meat. Cholesterol is carried through the body attached to protein. These proteins are called a lipoprotein. There are two main types of lipoproteins. High-density lipoprotein (HDL) is a type of lipoprotein responsible for transporting cholesterol away from the body's tissues and back to the liver, where it is either broken down or eliminated in the bile. Thus, HDL It often referred to as ‘good cholesterol’, given that it helps to remove the excess cholesterol from the bloodstream. On the other hand, Low-density lipoprotein (LDL) can carry cholesterol to the tissue of the body but, if it is too much, it starts to accumulate around artery walls. As a result, it can eventually form blood clots. For this reason, LDL is often referred to as “bad cholesterol”. Both HDL and LDL cholesterol are usually measured millimoles (mmol) per litre (L) of blood. The values for systolic blood pressure represent the mean values of the last three valid measurements taken by a registered nurse at the respondent’s house. Glycated haemoglobin (HbA1c) is a form of haemoglobin that reflects the average plasma glucose concentration over the past three months [112]. Haemoglobin binds with glucose in the red blood cells but, this process doesn’t happen simultaneously for all cells. Given that the lifespan of red blood cells is between eight to ten weeks, this reading is taken quarterly. HbA1c is the leading indicator for the diagnosis of diabetes. It can be measured in

percentage (%) or millimoles per mole (mmol/mol). In our sample, both measures were used, such that we had to convert the Hba1c values expressed in mmol/mol to percentages to satisfy the UKPDS-OM2 input requirements. The White Blood Cell count (WBC) enumerates the number of immune system cells, protecting the body against infections [113]. Haemoglobin refers to the red protein found inside the red blood cells that carry oxygen from the lungs to tissues in the body and transport carbon dioxide back to the lungs [114]. The estimated Glomerular Filtration Rate (eGFR) indicates the flow rate of filtered fluid through the kidney. It is a derived measurement, which can be obtained by formulas using standard blood-test results. Information about this biomarker was not available during the nurse module and thus retrieved using the following regression equation: eGFR = 134.8 – 0.758* age – 1.757*HbA1c – 0.235*BMI + 0.073*SBP [115].

#### 3.2.1.2 Outputs

The outputs provided by the model are divided into two different categories: health outcomes and costs.

##### 3.2.1.2.1 Outputs health outcomes

Life expectancy and Quality Adjusted Life Expectancy (QALE) are health outcomes of interest. Note that, while gains in life expectancy are a well-established measure of benefit, QALE also considers the quality of life of the individuals. QALE is calculated by weighting the lifetime survival function by the mean utility of quality of life for each year and then summing the results across a participant's remaining lifetime [116]. In this sense, QALE is a lifetime health measure with quality-adjusted life years (QALY) as its counting unit. Given that diabetes complications can have severe consequences, quality of life is a crucial aspect that needs to be incorporated into the analysis.

#### 3.2.1.2.2 Outputs costs

Among the costs, the outputs consist of cumulative therapy costs, cumulative complications costs and cumulative total costs. The definition of complication costs is self-explanatory and indicates the costs associated with the set of complications included in the model: ischemic heart disease (IHD), myocardial infarction (MI), heart failure, stroke, amputation, blindness, renal failure, and ulcer. Both costs arise when the complication is experienced, and the model considers costs occurring in the subsequent years. Different default values are provided according to age and gender. For example, therapy costs are associated with the medications for type 2 diabetes, and the total cost is simply the sum of the previous two costs items.

### 3.2.1.3 How the Model Works

Patients start to populate the model with a given set of demographic characteristics and risk factors. Once these characteristics and risk factors are entered into the model for each patient, the simulations start, and the model's first cycle begins [43, 96]. The probability of experiencing one or more of the seven complications included in the model by the patients is given by a set of equations [43, 117]. Each of these equations describes the occurrence probability of a specific complication. This probability is compared with a random number drawn from a uniform distribution ranging from 0 to 1. The event occurs if the probability of experiencing a complication is greater than the random number. Consequently, two different scenarios may arise. If the event is fatal, life years and quality-adjusted years are calculated. If the event is not fatal, the patient’s risk factors and history of the diabetes-related event are updated, and a new cycle starts again [43]. Thus, the model takes account of seven different complications that can also co-occur. To conclude this section, it is essential to note that the event

equations are randomly ordered. This means that any of the equations describing the set of complications can be experienced by the patients as a first event. This has been done to make the model more realistic, and because these events are competing for risks, e.g., if a patient dies within a cycle of the model, they can have no additional events [96]. To take this into account, the equations are run in random order. Moreover, using time-varying covariates indicating a patient's previous history of complications made it possible to model the linkage between different diabetes adverse events [43]. As already noted in the previous section, accounting for the interdependence between complications is a crucial component that needs to be addressed in diabetes modelling to make the model more consistent [102].

#### 3.2.1.4 How the models deal with uncertainty

The UKPDS-OM2 is a patient-level stochastic simulation tool that uses Monte Carlo techniques. When comparing risk equations' probabilities with a random number to determine whether an event will occur, some random noise might be generated, which can cause two identical patients to experience different outcomes just by pure chance. This random noise is referred to as Monte Carlo Error (MCE), and it can be reduced, if not eliminated, by Increasing the number of Monte-Carlo trials above a certain level. As a rule of thumb, at least 5,000 replications are usually needed to minimize concerns around MCE [118]. The UKPDS-OM2 authors dealt with this source of uncertainty by bootstrapping with replacement the original patient-level data from the UKPDS trial. This allowed them to build confidence intervals around all the outcomes provided by the model (Life Expectancy, Quality-Adjusted Life-Expectancy, Therapy Cost, Complication Costs, total cost). In addition, with the UKPDS-OM2, MCE was removed so that the confidence interval about the model's outputs solely reflects uncertainty

around the parameter estimates [117]. This can be achieved if a sufficient number of loops are performed. The MCE for a specified outcome is calculated as the standard deviation of the outcomes across the number of Monte-Carlo trials, $SD_N$, divided by the square root of the numbers of trials:

$MCE_N = SD_N / \sqrt{N}$ For $i = 1, \ldots,$ *n loops*

Past experimentation suggests that 5,000 or more loops are required.

## 3.3 Data: the ELSA cohort

Patient-level data from the ELSA cohort were entered into the UKPDS-OM2. The final cohort used to populate the model is the same used in the analysis of chapter 2. Depending on the inputs considered, I had a different percentage of missing data reported in table 3.3 below.

| Variable | Missing | Total | Missing (%) |
|---|---|---|---|
| | | | |
| Age | 0 | 91 | 0 |
| Gender | 0 | 91 | 0 |
| Smoking | 0 | 91 | 0 |
| Duration | 0 | 91 | 0 |
| Time-preferences | 0 | 91 | 0 |
| Risk-preferences | 0 | 91 | 0 |
| Weight | 11 | 91 | 12.09 |
| Blood-pressure | 17 | 91 | 18.68 |
| Heart rate | 17 | 91 | 18.68 |
| Hdl | 21 | 91 | 23.08 |
| Hba1c | 21 | 91 | 23.08 |
| Wbc | 21 | 91 | 23.08 |
| Haemoglobin | 21 | 91 | 23.08 |
| Ldl | 25 | 91 | 27.47 |

**Table 3-3 amount of missing data for each variable with relative percentages from the ELSA cohort**

In chapter 2 complete case analysis i.e., listwise deletion was performed therefore complete data were available for age, gender, smoking, ethnicity, time and risk preferences. However, the ELSA nurse module i.e. – the module from

which the information on biomarkers used in this analysis were retrieved - was only collected for a subsample of the ELSA participants. Consequently, depending on the biomarker considered, different percentages of missing values were observed. The percentage of missing values ranged from 27.47% (highest percentage) for LDL to 12.09 % (lowest percentage) for weight.

### 3.3.1 Multiple imputations

The UKPDS inputs workbook requires complete data for each participant. Otherwise, the model could not run. Therefore, according to most modern approaches to missing data techniques in cost-effectiveness analysis [119] [120], I have decided to deal with missing data by performing a multiple imputation by five chained equations. This procedure will help minimise bias and maximise the use of available information. Eight variables were registered for the imputation: HLD, LDL, systolic blood pressure, HbA1c, weight, heart rate, WBC, and haemoglobin. Since all of these variables are continuous, a linear regression imputation method was employed using the available demographic characteristics, age, gender, ethnicity, smoking and duration as auxiliary variables. The number of datasets to be generated was set to be equal to five. Above this value, there are only meagre gains in the precision of the estimates but higher computational costs [121-124]. Following the multiple imputation procedure, five copies of the original dataset were created, with the missing values replaced by the imputed values. These were sampled from the relevant distribution determined by the observed data. A table of summary statistics 3.4 and histograms of the imputed dataset (Appendix B1) show, that despite minor differences, the original and imputed datasets are comparable overall. These newly created multiple ‘complete’ datasets were subsequently entered into the UKPDS model. The model was run five times to obtain five different estimates of

each health and cost outcome, i.e., life expectancy, QALE, therapy costs, complication costs and total costs. Means of the resulting estimates were recorded and afterwards combined using the Rubin rule. One advantage of this procedure is that it considers the within iteration std. error and between iteration std. errors simultaneously. This entire procedure, allowed to produce overall confidence intervals reflecting the uncertainty of having to impute the missing values.

| | M = 0(original data) | m = 1 | m = 2 | m = 3 | m = 4 | m = 5 |
|---|---|---|---|---|---|---|
| Blood HDL level (mmol/l) | | | | | | |
| Mean (SD) | 1.40 (0.31) | 1.41 (0.31) | 1.38 (0.31) | 1.38 (0.33) | 1.40 (0.30) | 1.39 (0.32) |
| Median (Q1, Q3) | 1.4 (1.2, 1.6) | 1.4 (1.2, 1.7) | 1.3 (1.1, 1.6) | 1.4 (1.2, 1.6) | 1.4 (1.2, 1.6) | 1.3 (1.2, 1.6) |
| Min, Max | 0.9, 2.3 | 0.9, 2.3 | 0.8, 2.3 | 0.8, 2.3 | 0.9, 2.3 | 0.8, 2.3 |
| N (% Missing) | 70 (23.1%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| Blood LDL level (mmol/l) | | | | | | |
| Mean (SD) | 3.45 (1.28) | 3.49 (1.42) | 3.40 (1.18) | 3.58 (1.30) | 3.46 (1.21) | 3.53 (1.28) |
| Median (Q1, Q3) | 3.3 (2.4, 4.6) | 3.4 (2.4, 4.6) | 3.2 (2.4, 4.2) | 3.6 (2.6, 4.6) | 3.3 (2.4, 4.5) | 3.6 (2.5, 4.6) |
| Min, Max | 1.0, 6.6 | -0.1, 7.2 | 1.0, 6.6 | 0.9, 6.6 | 1.0, 6.6 | 0.5, 6.6 |
| N (% Missing) | 66 (27.5%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| Systolic blood pressure (mmHg) | | | | | | |
| Mean (SD) | 132.39 (16.29) | 130.82 (18.65) | 130.93 (17.74) | 131.16 (17.77) | 131.69 (16.86) | 130.24 (16.71) |
| Median (Q1, Q3) | 131.5 (120.0, 141.5) | 130.0 (119.5, 142.0) | 130.0 (119.5, 142.0) | 129.5 (119.5, 141.5) | 130.0 (119.5, 141.5) | 128.5 (119.5, 140.9) |
| Min, Max | 97.0, 176.5 | 78.2, 176.5 | 82.3, 176.5 | 79.1, 180.4 | 97.0, 176.5 | 97.0, 176.5 |
| N (% Missing) | 74 (18.7%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| Blood glycated haemoglobin level (%) | | | | | | |
| Mean (SD) | 6.57 (1.27) | 6.47 (1.26) | 6.61 (1.20) | 6.55 (1.27) | 6.53 (1.23) | 6.55 (1.31) |
| Median (Q1, Q3) | 6.1 (5.7, 7.3) | 6.1 (5.7, 7.2) | 6.3 (5.7, 7.3) | 6.2 (5.7, 7.3) | 6.2 (5.7, 7.3) | 6.1 (5.7, 7.3) |
| Min, Max | 5.1, 11.0 | 3.8, 11.0 | 4.9, 11.0 | 3.3, 11.0 | 4.7, 11.0 | 4.0, 11.0 |
| N (% Missing) | 70 (23.1%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| Respondent Weight (Kgs) | | | | | | |
| Mean (SD) | 86.34 (17.15) | 85.81 (17.76) | 86.24 (17.99) | 87.12 (16.96) | 85.13 (17.04) | 86.43 (16.97) |
| Median (Q1, Q3) | 86.4 (71.3, 95.3) | 85.6 (70.2, 95.6) | 86.4 (71.7, 95.8) | 86.5 (72.7, 95.6) | 85.5 (70.2, 94.6) | 86.4 (71.7, 95.6) |
| Min, Max | 52.0, 130.0 | 52.0, 132.7 | 40.7, 130.0 | 52.0, 130.0 | 51.2, 130.0 | 52.0, 130.0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| N (% Missing) | 80 (12.1%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| Heart rate | | | | | | |
| Mean (SD) | 55.59 (12.87) | 55.11 (13.05) | 55.67 (13.31) | 54.41 (13.43) | 55.23 (14.19) | 54.34 (12.77) |
| Median (Q1, Q3) | 54.5 (45.5, 63.0) | 54.5 (45.5, 63.0) | 54.5 (45.5, 64.5) | 54.0 (45.5, 61.5) | 54.5 (45.5, 64.0) | 53.5 (45.5, 61.5) |
| Min, Max | 27.0, 90.5 | 27.0, 90.5 | 24.2, 90.5 | 9.6, 90.5 | 27.0, 100.7 | 26.3, 90.5 |
| N (% Missing) | 74 (18.7%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| White blood cell count (x 10^9 cells/litre) | | | | | | |
| Mean (SD) | 6.79 (2.07) | 6.71 (2.25) | 6.56 (2.35) | 6.85 (2.14) | 6.80 (1.97) | 6.82 (2.09) |
| Median (Q1, Q3) | 6.5 (5.3, 8.0) | 6.4 (5.1, 8.2) | 6.1 (4.9, 8.0) | 6.5 (5.1, 8.5) | 6.6 (5.4, 8.1) | 6.6 (5.3, 8.4) |
| Min, Max | 3.6, 12.0 | 0.7, 12.0 | 2.1, 15.2 | 3.4, 12.0 | 2.5, 12.0 | 3.2, 12.0 |
| N (% Missing) | 70 (23.1%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |
| Blood haemoglobin level (g/dl) | | | | | | |
| Mean (SD) | 14.30 (1.11) | 14.39 (1.08) | 14.41 (1.21) | 14.31 (1.04) | 14.42 (1.15) | 14.40 (1.18) |
| Median (Q1, Q3) | 14.4 (13.5, 15.1) | 14.6 (13.5, 15.2) | 14.5 (13.5, 15.2) | 14.4 (13.6, 15.0) | 14.5 (13.5, 15.2) | 14.4 (13.5, 15.2) |
| Min, Max | 11.7, 16.5 | 11.7, 16.5 | 11.7, 17.2 | 11.7, 16.5 | 11.7, 16.9 | 11.7, 17.3 |
| N (% Missing) | 70 (23.1%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) | 91 (0.0%) |

**Table 3-4 comparisons of summary statistics between the original dataset with the imputed datasets(m=5).**

### 3.3.2 Study size

The final dataset, entered in the UKPDS-OM2, counts 91 unique individuals. Given that T2DM is a life-long condition, the variable that implied the *longer time trade-offs* (2 weeks vs 2 months as described in section 2.3.1.3) was preferred over the variable which involves a *shorter time trade-off* (two weeks vs one month). Subsequently, subjects were divided into two groups following the category for the variable *longer time trade-offs* created in chapter 2. The first group comprised individuals characterised by low time-preferences rates (LTP) than the second group of subjects, characterised by high time-preference rates (HTP). Please refer to section 2.3.1.3 for more detail on how these categories were created. It is important to note that preferences did not enter the model directly i.e., these two groups were created by splitting the sample according to the values of the longer time-trade off variable. The usual *a priori expectation* is that participants from the category with high time preferences rates are less in control of their T2DM than their low time preferences rates counterparts. Consequently, it is reasonable to predict that individuals who can control their diabetes better i.e., low time preference rates will have more favourably long-term health outcomes and possibly lower total costs concerning individuals who do not master T2DM management to the same extent.

Similarly, to what has been described above for the time preferences variable, I have also split the representative sample into two groups according to individuals' risk preferences. This process was done always following the category created in section 2.3.1.5. Hence, two groups were created even in this case: *risk-averse* individuals (RA) and another group of *risk-lover* participants (RL). The a priori expectation is that *risk-averse* individuals are more efficient in managing their T2DM. Consequently, it can be assumed that risk-averse individuals will be more

prone to avoid a particularly unhealthy behaviour and, thus, more likely to experience better outcomes in the long run than their risk-lover counterparts.

### 3.3.3 Descriptive characteristics

#### 3.3.3.1 Descriptive characteristics by time preference group

Descriptive characteristics for the final sample are presented separately for each time preference group in table 3.5. This table includes mean, median, first and third interquartile range measures for the original dataset e.g., m =0. As suggested by the fourth column, individuals from the low time-preference group are slightly younger on average compared their high time preference counterpart (63.77 vs 64.08 mean age for each group), however this difference is not statistically significant (p-value = 0.803). Similarly, differences in the proportion of males and females between the two group are also not statistically significant (p-value 0.626). With regards of the biomarkers no statistically significant difference was detected among the two groups of low and high time preferences rates respectively (significance level 0.05).

**Table 3-5 Descriptive characteristics for the final sample used in the simulation by time preference group.**

| | low time preferences rates | high time preferences rate | p-value |
|---|---|---|---|
| | (N = 39) | (N = 52) | |
| Age (in years/ continuous) | | | 0.803 |
| Mean (SD) | 63.77 (5.67) | 64.08 (5.91) | |
| Median (Q1, Q3) | 62.0 (59.0, 69.0) | 64.5 (60.0, 68.0) | |
| Blood HDL level (mmol/l) | | | 0.913 |
| Mean (SD) | 1.40 (0.30) | 1.40 (0.32) | |
| Median (Q1, Q3) | 1.3 (1.2, 1.5) | 1.4 (1.2, 1.6) | |
| Blood LDL level (mmol/l) | | | 0.241 |
| Mean (SD) | 3.66 (1.48) | 3.29 (1.08) | |
| Median (Q1, Q3) | 3.4 (2.4, 5.0) | 3.1 (2.3, 4.2) | |
| Systolic blood pressure (mmHg) | | | 0.730 |
| Mean (SD) | 133.18 (16.71) | 131.84 (16.16) | |

**Table 3-5 Descriptive characteristics for the final sample used in the simulation by time preference group.**

| | | | |
|---|---|---|---|
| Median (Q1, Q3) | 133.8 (120.0, 141.5) | 129.5 (119.8, 141.8) | p-value |
| Blood glycated haemoglobin level (%) | | | 0.467 |
| Mean (SD) | 6.44 (1.16) | 6.66 (1.34) | |
| Median (Q1, Q3) | 5.9 (5.7, 7.2) | 6.2 (5.7, 7.3) | |
| Weight (Kgs) | | | 0.806 |
| Mean (SD) | 85.75 (16.71) | 86.73 (17.61) | |
| Median (Q1, Q3) | 86.0 (73.0, 91.8) | 86.4 (70.0, 96.6) | |
| Heart rate (beats per minute) | | | 0.962 |
| Mean (SD) | 55.50 (11.60) | 55.65 (13.81) | |
| Median (Q1, Q3) | 54.8 (45.5, 61.5) | 53.3 (46.0, 65.3) | |
| White blood cell count (x 10^9 cells/litre) | | | 0.643 |
| Mean (SD) | 6.66 (1.81) | 6.89 (2.26) | |
| Median (Q1, Q3) | 6.7 (5.5, 8.0) | 6.4 (5.3, 8.4) | |
| Blood haemoglobin level (g/dl) | | | 0.863 |
| Mean (SD) | 14.33 (1.00) | 14.28 (1.20) | |
| Median (Q1, Q3) | 14.3 (13.7, 14.8) | 14.5 (13.3, 15.1) | |
| Gender (male/female) | | | 0.626 |
| female | 23 (59.0%) | 28 (53.8%) | |
| male | 16 (41.0%) | 24 (46.2%) | |
| Ethnicity (white/non-white) | | | 0.384 |
| white | 39 (100.0%) | 51 (98.1%) | |
| non-white | 0 (0.0%) | 1 (1.9%) | |
| Smoking (yes/no) | | | 0.807 |
| no | 33 (84.6%) | 43 (82.7%) | |
| yes | 6 (15.4%) | 9 (17.3%) | |
| N=91 | | | |

*Note: p-values refer to t-tests for continuous variables and chi-squared tests for categorical variables.*

### 3.3.3.2 Descriptive characteristics by risk preference group

Table 3.6 describes baseline characteristics for the final sample by risk preference group. Similarly, to what was observed for the time preference variable there are no statistically significant differences between the two groups of risk-averse and risk lovers individuals apart from systolic blood-pressure (p-value = 0.039). This difference in blood pressure may be related to the fact that risk lover participants were more likely to attend the blood pressure check as

stated in Table 2.27 in chapter 2 (Model 4; Odds Ratio 1.999; 95% 1.227,3.257; p-value<0.001). However, this difference is unlikely to affect the results of the current analysis since the finding mentioned above was related to a sample that included participants with at least one chronic condition (such as T2DM, high blood pressure, and high cholesterol) and was not statistically significant in the sample that only included participants diagnosed with T2DM (which is the sample used in the present analysis) as described in Table 2.18.

**Table 3-6 Descriptive characteristics for the final sample used in the simulation by risk preference group.**

| | Risk averse (N=70) | Risk lovers(N=21) | p-value |
|---|---|---|---|
| Age (in years/ continuous) | | | 0.826 |
| Mean (SD) | 63.87 (6.09) | 64.19 (4.73) | |
| Median (Q1, Q3) | 63.5 (59.0, 69.0) | 63.0 (60.0, 67.0) | |
| Blood HDL level (mmol/l) | | | 0.760 |
| Mean (SD) | 1.39 (0.27) | 1.42 (0.45) | |
| Median (Q1, Q3) | 1.4 (1.2, 1.6) | 1.4 (1.0, 1.7) | |
| Blood LDL level (mmol/l) | | | 0.907 |
| Mean (SD) | 3.46 (1.26) | 3.42 (1.39) | |
| Median (Q1, Q3) | 3.4 (2.4, 4.5) | 2.8 (2.4, 4.6) | |
| Systolic blood pressure (mmHg) | | | 0.039 |
| Mean (SD) | 134.59 (15.45) | 125.53 (17.35) | |
| Median (Q1, Q3) | 134.3 (123.5,142.8) | 121.5 (114.0,137.5) | |
| Blood glycated haemoglobin level (%) | | | 0.501 |
| Mean (SD) | 6.62 (1.26) | 6.36 (1.32) | |
| Median (Q1, Q3) | 6.2 (5.7, 7.3) | 5.8 (5.4, 7.4) | |
| Weight (Kgs) | | | 0.177 |
| Mean (SD) | 87.74 (16.75) | 81.52 (18.14) | |
| Median (Q1, Q3) | 89.0(75.0,95.6) | 76.2 (68.9, 92.2) | |
| Heart rate (beats per minute) | | | 0.616 |
| Mean (SD) | 56.02 (11.97) | 54.25 (15.67) | |
| Median (Q1, Q3) | 54.5 (46.8, 62.8) | 50.3 (43.5, 64.5) | |
| White blood cell count (x 10^9 cells/litre) | | | 0.270 |
| Mean (SD) | 6.93 (2.06) | 6.24 (2.11) | |
| Median (Q1, Q3) | 6.7 (5.3, 8.2) | 5.7 (5.0, 8.0) | |
| Blood haemoglobin level (g/dl) | | | 0.086 |
| Mean (SD) | 14.19 (1.12) | 14.76 (0.99) | |
| Median (Q1, Q3) | 14.3 (13.4, 14.9) | 14.8 (14.0, 15.3) | |

| | | | |
|---|---|---|---|
| Gender (male/female) | | | 0.263 |
| female | 37 (52.9%) | 14 (66.7%) | |
| male | 33 (47.1%) | 7 (33.3%) | |
| Ethnicity (white/non-white) | | | 0.582 |
| white | 69 (98.6%) | 21 (100.0%) | |
| non-white | 1 (1.4%) | 0 (0.0%) | |
| Smoking (yes/no) | | | 0.718 |
| no | 59 (84.3%) | 17 (81.0%) | |
| yes | 11 (15.7%) | 4 (19.0%) | |
| N = 91 | | | |

*Note: p-values refer to t-tests for continuous variables and chi-squared tests for categorical variables.*

## 3.4 Results

The following sections, 3.4.1 and 3.4.2, describe the results from the UKPDS-OM2 for both time and risk preferences analyses, respectively. As described in section 3.2.1 about the methods, five different outcomes will be provided for each analysis. These outcomes are divided into two categories of health outcomes and costs. Health outcomes include life expectancy and QALE, while the latter category of costs, entails therapy cost, cost of complications and total costs[2]. Alongside the model's outcomes, estimates of the total variance (divided between within imputation variance and between imputation variance) and measures for relative efficiency will also be reported.

### 3.4.1 Time preferences

The results of the time preferences analysis are presented in five distinct sections (from 3.4.1.1 to 3.4.1.5), each showing one specific outcome: life expectancy, QALE, therapy costs, complications costs and total costs.

[2] Because the model's output reflects five different imputations, the sum of therapy cost plus the cost of complications is not perfectly equal to the total cost.

### 3.4.1.1 Life expectancy

Life expectancy was 12.957 years (95% CIs 12.377 to 13.537) for the group with high time preferences rates compared to 13.017 years (95% CIs 12.366 to 13.669) for the group characterised by low time preferences rates Table 3.7. This equals an overall difference of 0.06 years between the two groups. However, as can be seen from the overlapping CIs the difference in the mean life expectancy between the two group was not statistically significant. The between imputation variance is greater than the within imputation variance for both the high and low time preferences groups. This, coupled with the relative efficiency close to 1, provides reassurance that five imputations were sufficient to produce reliable estimates of the missing values.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Life expectancy (years)** | **Between** | **Within** | **Total** | | | | |
| **High TP** | 0,0053 | 0.0810 | 0.0874 | 760.79 | 0.0782 | 0.074 | 0.985 |
| **Low TP** | 0.013 | 0.093 | 0.109 | 191.37 | 0.169 | 0.153 | 0.970 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Life expectancy (years)** | | | | | | | |
| **High TP** | 12.957 | 0.295 | 12.377 | 13.537 | 760.79 | 12.881 | 13.066 |
| **Low TP** | 13.017 | 0.330 | 12.366 | 13.669 | 191.37 | 12.849 | 13.136 |

**Table 3-7 UKPDS-OM2 variance information and life expectancy estimate for time preference.**

### 3.4.1.2 Quality Adjusted Life Years

As reported by Table 3.8, total QALE was also very slightly more prominent for the individuals pertaining from the low time preference group (10.357 years; 95% 9.814 to 10.763) compared to the group of individuals who showed high time

preferences (10.289 years; 95% CIs 9.847 to 10.847). However, this difference between the two groups which amounts to 0.068 QALE in favour of the low-time preference group was not significant at 5% level. As was previously the case for life expectancy also for QALE, the larger values of the within variance compared to the between variance and the proximity of the value of relative efficiency to 1 provide reassurance that the number of imputations employed to replace missing values for the biomarkers were appropriate.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **QALE** | **Between** | **Within** | **Total** | | | | |
| **High TP** | 0.004 | 0.054 | 0.058 | 680.03 | 0.088 | 0.084 | 0.983 |
| **Low TP** | 0.007 | 0.056 | 0.064 | 250.96 | 0.144 | 0.133 | 0.974 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Maxi** |
| **Life expectancy** | | | | | | | |
| **High TP** | 10.289 | 0.242 | 9.814 | 10.763 | 608.030 | 10.221 | 10.383 |
| **Low TP** | 10.357 | 0.254 | 9.847 | 10.847 | 250.960 | 10.225 | 10.426 |

**Table 3-8 UKPDS-OM2 variance information and QALE estimate for time preferences.**

### 3.4.1.3 Therapy costs

Therapy costs were £ 3431.21 (95% CIs 3163.02 to 3699.4) for the group with low time preferences and £ 1786.24 (95% CIs 1640.13 to 1932.36) for the group with high time preferences, with a difference of £ 1644.97 between the two groups, i.e., therapy costs were £ 1644.97 higher for the group populated by

individuals with low time preferences. This difference was statistically significant at 5% level. The index of relative efficiency is consistently close to 1 for each group.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Therapy costs** | **Between** | **Within** | **Total** | | | | |
| **High TP** | 1862.36 | 2640.00 | 4874.83 | 19.032 | 0.847 | 0.508 | 0.908 |
| **Low TP** | 3941.64 | 13215 | 17945 | 57.573 | 0.358 | 0.288 | 0.946 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Therapy costs** | | | | | | | |
| **High TP** | 1786.24 | 69.82 | 1640.13 | 1932.36 | 19.032 | 1725.81 | 1841.80 |
| **Low TP** | 3431.21 | 133.96 | 3163.02 | 3699.4 | 57.573 | 3341.35 | 3502.49 |

**Table 3-9 UKPDS-OM2 variance information and parameter estimates for therapy costs.**

### 3.4.1.4 Complications costs

Table 3.10 describes the estimated complications costs for the participants living with T2DM from the ELSA cohort. Complications costs were £ 31,143 (95% CIs 28808.2 to 33477.0) for individuals from the category with low time preferences and £ 30,599 (95% 28769.8 to 32427.3) for those with high time preferences. The difference in complications costs between the groups (£ 544) was not statistically significant at 5 % level.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Complications costs (£)** | **Between** | **Within** | **Total** | | | | |
| **High TP** | 82182 | 765123 | 863741 | 306.84 | 0.1288 | 0.1198 | 0.9765 |
| **Low TP** | 195341 | 1160033 | 1394442 | 141.55 | 0.2020 | 0.1796 | 0.9653 |

| Parameter estimate (5 imputations) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Complications costs (£)** | | | | | | | |
| **High TP** | 30599 | 929.37 | 28769.8 | 32427.3 | 306.84 | 30162 | 30892 |
| **Low TP** | 31143 | 1180.86 | 28808.2 | 33477.0 | 141.55 | 30710 | 31729 |

**Table 3-10 UKPDS-OM2 variance information and parameter estimates for complications costs.**

### 3.4.1.5 Total costs

As reported by Table 3.11, which summarises the output for total costs, individuals from the low TP group had higher total costs (£ 34,574; 95% CIs 29907.7 to 39239.9) compared to the high TP group (£ 32,385; 95% CIs 28814.7 to 35955.0) with a discrepancy of £ 2,189 between the two groups. Although, based on the overlapping 95% confidence intervals, there is no statistically significant difference at a 5% level between the means of the two groups.

| Variance information (5 imputations) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Total costs (£)** | **Between** | **Within** | **Total** | | | | |
| **High TP** | 107983 | 3185329 | 3314909 | 2617.7 | 0.04068 | 0.0398 | 0.9920 |
| **Low TP** | 250801 | 5357185 | 5658146 | 1413.8 | 0.056179 | 0.0545 | 0.9892 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Total costs (£)** | | | | | | | |
| **High TP** | 32385 | 1820.68 | 28814.7 | 35955.0 | 2617.7 | 31887 | 32733 |
| **Low TP** | 34574 | 2378.68 | 29907.7 | 39239.9 | 1413.8 | 34051 | 35231 |

**Table 3-11 UKPDS-OM2 variance information and parameter estimates for total costs.**

## 3.4.2 Risk preferences

The following sections, from 3.4.2.1 to 3.4.2.5, describe the results of the risk preference analysis. Each section refers to a different outcome, i.e., life expectancy, QALE, therapy costs, complications costs, and total costs.

### 3.4.2.1 Life expectancy

The first set of results examined the impact of risk preferences on life expectancy Table 3.12. Life expectancy was 13.40 years (95% CIs 12.912 to 13.890) for the risk-averse participants compared to 13.11 years (95% CIs 12.527 to 13.700) for their risk-lover counterparts. Therefore, there was no statistically significant difference in life expectancy between the two groups of risk-averse and risk-lover participants.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Life expectancy (years)** | **Between** | **Within** | **Total** | | | | |
| **Risk lovers** | 0.0081 | 0.07921 | 0.0889 | 332.75 | 0.1231 | 0.1149 | 0.9775 |
| **Risk averse** | 0.0060 | 0.0544 | 0.0617 | 286.62 | 0.1339 | 0.1242 | 0.9757 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Life expectancy (years)** | | | | | | | |
| **Risk lover** | 13.1138 | 0.2982 | 12.527 | 13.700 | 332.75 | 13.010 | 13.213 |
| **Risk averse** | 13.401 | 0.2484 | 12.912 | 13.890 | 286.62 | 13.315 | 13.521 |

**Table 3-12 UKPDS-OM2 variance information and life expectancy estimates for time preference**

### 3.4.2.2 Quality Adjusted Life Years

Similarly, to what has been previously described in the section about life expectancy, further results confirmed that although total QALE was slightly more prominent for the group characterised by risk-averse participants (10.657 QALE;

95% CIs 10.249 to 11.066) compared to the group populated by risk-lover individuals (10.413 years 95% 9.9402 to 10.886) Table 3.13, however this difference did not reach statistical significance.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **QALE** | **Between** | **Within** | **Total** | | | | |
| **Risk Lovers** | 0.0061 | 0.0503 | 0.0577 | 247.62 | 0.1456 | 0.1340 | 0.9738 |
| **Risk averse** | 0.0046 | 0.0373 | 0.0429 | 235.09 | 0.1500 | 0.1377 | 0.9731 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **QALE** | | | | | | | |
| **Risk lover** | 10.413 | 0.2402 | 9.9402 | 10.886 | 247.62 | 10.316 | 10.497 |
| **Risk averse** | 10.657 | 0.207 | 10.249 | 11.066 | 235.09 | 10.577 | 10.755 |

**Table 3-13 UKPDS-OM2 variance information and parameter estimates for QALE.**

### 3.4.2.3 Therapy costs

In contrast to participants in the risk-lover group, individuals included in the risk-averse group had higher therapy costs, as Table 3.14 illustrates. The average therapy costs over a lifetime were £ 3280.44 for risk-averse participants (95% CIs 2725.91 to 3834.97) compared to an average of £ 1826.46 for their risk-lover equivalent (95% CIs 1762.53 to 1890.40). Therefore, it has been found that there is a statistically significant discrepancy of £ 1453 in the average therapy costs between the two groups.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Therapy costs (£)** | **Between** | **Within** | **Total** | | | | |
| **Risk lovers** | 369.196 | 477.467 | 920.503 | 17.268 | 0.9278 | 0.5324 | 0.9037 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Risk averse** | 34238 | 2724.80 | 43810 | 4.5482 | 15.078 | 0.9542 | 0.8397 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Therapy costs (£)** | | | | | | | |
| **Risk lover** | 1826.46 | 30.339 | 1762.53 | 1890.40 | 17.268 | 1802.00 | 1852.78 |
| **Risk averse** | 3280.44 | 209.308 | 2725.91 | 3834.97 | 4.5482 | 2963.81 | 3421.65 |

**Table 3-14 UKPDS-OM2 variance information and parameter estimates for therapy costs.**

### 3.4.2.4 Complications costs

As shown in Table 3.15, the mean complications cost was £ 31,983 (95 CIs 30100 to 33685) for risk-averse participants compared to £ 31,034 (95% CIs 29224 to 32844) for the people who populated the risk lovers group. Although a difference of £ 949 was found between these two groups, it did not reach statistical significance.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Complications costs (£)** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **QALE** | **Between** | **Within** | **Total** | | | | |
| **Risk lovers** | 25446 | 821919 | 852454 | 3117.5 | 0.0371 | 0.0364 | 0.9927 |
| **Risk averse** | 93006 | 715426 | 827033 | 219.65 | 0.1560 | 0.1427 | 0.9722 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Complications costs (£)** | | | | | | | |
| **Risk lover** | 31034 | 923.28 | 29224 | 32844 | 3117.5 | 30839 | 31188 |
| **Risk averse** | 31893 | 909.41 | 30100 | 33685 | 219.65 | 31651 | 32316 |

**Table 3-15 UKPDS-OM2 variance information and parameter estimates for complications costs.**

### 3.4.2.5 Total costs

As reported in Table 3.16, the total cost was £ 35,173 (95% CIs 33103 to 37243) for the risk-averse group, whereas participants from the risk-lover group had average total costs of £ 32,861 (95% 30993 to 34728). Despite a £2,312 difference in total costs between risk-averse and risk-loving participants, the overlapping 95% CIs did not indicate statistical significance.

| **Variance information (5 imputations)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | **Variance** | | | **DF** | **Relative increase in variance** | **Fraction missing information** | **Relative efficiency** |
| **Total costs (£)** | **Between** | **Within** | **Total** | | | | |
| **Risk lover** | 28446 | 873180 | 907316 | 2825.9 | 0.0390 | 0.0383 | 0.9923 |
| **Risk averse** | 191688 | 855174 | 1085199 | 89.028 | 0.2689 | 0.2290 | 0.9561 |
| **Parameter estimate (5 imputations)** | | | | | | | |
| **Parameter** | **Estimate** | **SE** | **95% CIs** | | **DF** | **Min** | **Max** |
| **Total costs (£)** | | | | | | | |
| **Risk lover** | 32861 | 952.53 | 30993 | 34728 | 2825.9 | 32641 | 33020 |
| **Risk averse** | 35173 | 1041.72 | 33103 | 37243 | 89.028 | 34615 | 35737 |

**Table 3-16 UKPDS-OM2 variance information and parameter estimates for total costs.**

## 3.5 Discussion

This study examined the impact of time and risk preferences on T2DM long-term health outcomes and costs. Results indicated no statistically significant difference in life expectancy or QALE between individuals with low or high time preferences. Similarly, those who were risk-averse and those who were risk-loving had similar estimates with no significant statistical difference between them. Additionally, there were no differences in costs between the two groups, except for therapy costs. Although not statistically significant, the overall results seem to suggest that participants from the low-time preference and risk-averse group have on average longer life expectancy, a slightly higher quality of life, and incur higher

therapy costs compared to their high-time preference and risk-lover analogues. However, this need to be interpreted with extreme caution because the estimates from the model did not reach statistical significance as signified by the overlapping confidence intervals. Unexpectedly and contrary to what has been observed consistently in the literature [82], there were no statistically significant differences in risk preferences by gender. However, this lack of effect may be due to using chi-squared tests [125], which are sensitive to sample sizes. Therefore, this result should be interpreted with caution.

The present study has several strengths. Firstly, it benefitted from the availability of measures for time and risk preference elicited trough a laboratory experiment which are not typically included in surveys. Secondly, it made use of a detailed disease progression model populated with a wide range of detailed biomarkers that allowed to extrapolate health and cost outcome with a lifetime horizon with great precision. Thirdly, the strategy to deal with missing data was thorough and included both parameter and imputation uncertainty. However, despite this thorough strategy another key limitation is represented by the fact that multiple imputation requires the data to be missing at random (MAR), which may not be especially plausible in certain context. Nevertheless, the nurse module was randomly administered among the ELSA participants, an aspect which provides a reasonable degree of reassurance that data were MAR.

Although previous studies have shown a link between risk and time preference and various T2DM self-management behaviours [28], including adherence [19], this study was unable to replicate these findings. A potential reason for this could be the limited sample size, resulting in insufficient statistical power. Therefore, further research with a larger sample size is warranted before the results from current study can have practical implication for policy and practice.

# Chapter 4
# Health investment decisions after a diagnosis of type 2 diabetes: Results from the English Longitudinal Study of Ageing (ELSA)

## 4.1 Introduction

As outlined in chapter 1, non-adherent behaviour to guidelines for managing type 2 diabetes (T2DM) has detrimental effects on many health outcomes, including reduced quality of life. What is more, they impose increased and potentially avoidable healthcare costs on an already resource-constrained NHS [126]. Modifiable lifestyle factors such as following a healthy diet, quitting smoking, and engaging in physical activity play a significant role in T2DM self-management strategies. Therefore, the usual practice recommended by the guidelines after T2DM diagnosis is to encourage behaviour change for newly diagnosed patients. In the UK, the standard first-line recommendations immediately following the diagnosis of T2DM involve healthy dietary advice, smoking cessation, curbing alcohol and increasing physical activity [14]. A diet rich in complex carbohydrates with a low glycaemic index and low in saturated fats can improve glycaemic control [44]. Such a diet can also promote weight loss and positively increase insulin sensitivity [127]. The benefits of quitting smoking, lowering alcohol consumption, and increasing physical activity are widely known. They are of particular importance for people living with T2DM which are six times as likely to suffer from cardiovascular diseases, three times more likely to experience kidney problems, and almost five times more likely to incur eye damage compared to the

general population. However, despite the overwhelming evidence [48, 49, 55, 87] showing the positive effects of following T2DM guidelines, in terms of lower risk of incurring T2DM complications and improved quality of life, it is not clear whether people change behaviour following the diagnosis. Diabetes is a silent condition, which can make newly diagnosed individuals question the need for behaviour change.

Although the evidence from both clinical trials and translational lifestyle interventions suggests that individuals change behaviour after T2DM diagnosis, it is not clear whether these positive effects can still be detected at a population level, outside of the context of these targeted interventions for promoting behaviour change [32]. Behaviour change is a salient aspect of T2DM self-management. Type 2 diabetes is a long-life condition where people provide up to 80% of their care. Therefore, a better understanding of whether and to what extent people with diabetes change their behaviour in response to a new diagnosis is crucial to advance the discussion on how to increase adherence to self-management behaviour. This is also emphasised by the Quality Outcomes Framework (QOF), which include physical activity status and smoking cessation amongst its indicator [128].

### 4.1.1 Objectives

By using the Grossman model as an underlying theoretical framework, this work will explore the research question of whether and to what extent the ‘health shock’ of a new diagnosis of T2DM is a sufficient trigger to motivate newly diagnosed patients to adhere to the behaviour change recommendations suggested by the guidelines for the management of T2DM. Adverse health events such the diagnosis of T2DM, provide individuals who experienced it, update information about the potential harmful consequences of their behaviour. As it will be

described more in detail in the section 4.1.3 about the theoretical framework, this in turn, would incentivize them to increase their investment in health by adopting a healthier lifestyle [46].

The main research question will be answered by using three different methods, as described more in detail in section 4.3 about the statistical analysis. The first methods will replicate the analysis performed by Hackett et al., 2018 in their recent longitudinal analysis on behaviour change after T2DM diagnosis [32]. Therefore, Generalized Estimating Equations (GEE) models, the same method applied by Hackett et al., 2018 will be implemented and described in subsection 4.3.1.1 In addition, a Random Intercept Logit (RE) model, the second approach, is introduced in the section below 4.3.2. which will address the conditional independence of the responses across different occasions for the same subject in a different manner with respect to the GEE estimation method. While population average model such as GEE, do take into account the dependence of the responses at different occasions for a given subject, they treat it more as a nuisance by simply specifing a working correlation whereas this dependence represents a central aspect in multilevel modelling [129]. In contrast, multilevel models like RE are able to model subject specific relationships and how they vary around the population average. This in turn will make the interpretation of the results fundamentally different compared to population average models like the one that will be employed in the GEE anaysis. Whereas GEE estimates reflects popualtion average probabilities conditioning only on the covariates, RE will estimate subject-specific probabilities, taking into account subject specific random intercepts ζj and the covariates. The latter (RE) effects are expected to be more extreme i.e., more different from zero. In consideration of the fact that the aim of the current analysis is looking at individual behaviour to a health shock

and not at a population response to a new treatment or public health promotion campaign, population-average models seem a less appropriate approach compared to RE to answer the research question of whether the 'health-shock' of a new T2DM diagnosis represents a teachable moment able to trigger bahaviour change in newly diagnosed ELSA participants. Finally, to adjust for the effect of possible confounders, a third method, in the form of a Propensity Score Matching (PSM) approach, will be adopted in section 4.3.1.3. People who develop T2DM may have different characteristics and behave differently than people who do not develop the same condition. Therefore, the decision to implement a PSM approach to adjust the analysis for possible confounders' effect. In particular it can be hypothesised that indivdual who will ultimaltely develop T2DM will have greater value in BMI and HbA1c at baseline, two crucial prognostic factors for diabetes.

Section 4.1.2 will outline several studies that addressed a similar research question that this work will answer. In contrast, section 4.1.3 will expand upon the underlying theoretical framework used throughout this chapter and its theoretical predictions.

### 4.1.2 Literature review

Several longitudinal studies have already tried to address the research questions of whether T2DM diagnosis can trigger behaviour change in newly diagnosed individuals; still, the evidence produced is mixed possibly with the only exception of smoking[3] [32, 45, 47, 49, 130-139]. A stream of European empirical literature looked at changes in smoking and diet. For instance, a study from Sweden

[3] The present literature review includes studies up to January 2020, the time at which the analysis was conducted. This coupled with the fact that it was not a systematic review implies that other relevant studies might have not been reported.

investigated change over time in vegetable, fruit and juice consumption in a prospective cohort of 23 953 middle-aged men [130]. Participants recently diagnosed with T2DM (1741 in total) increased their fruit and vegetable consumption by 0.9 serving a week [95% CI (0.38, 1.3)] compared to the group populated by individuals who did not receive such a diagnosis. However, a cohort of 4703 participants from the UK Whitehall II study did not replicate these findings since participants did not appear to improve their diet after being informed about their diabetic status [Odds Ratio [134]. A study from The Netherlands, which investigated lifestyle transitions among a cohort of 2184 respondents aged 55 to 85 from The Longitudinal Ageing Study Amsterdam, found no changes in health-protective behaviour in those with and without T2DM at six years of follow-up [140].Nevertheless, the proportion of people who reported sedentary behaviour increased in the short term (<= 2 years) from 28.1% to 46.9% among the participants diagnosed with T2DM within the timeframe of the data. A study of particular importance for the present work is research by Hackett et al., 2018 [32], which investigated health behaviour changes, e.g., smoking, physical activity, fruit and vegetable intake, sedentary behaviour and alcohol consumption, after T2DM diagnosis among a sample of 6,877 ELSA participants. The authors employed Generalized Estimating Equation (GEE) regression techniques and compared an intervention group of participants who self-reported a diagnosis of T2DM between waves 3 and 7 of the ELSA to a control group of participants who did not self-reported a diagnosis. Their findings showed limited evidence of behaviour change apart from a reduction in the percentage of people who reported to be current smokers (~4%) in the intervention group compared to the control group.

A recent study from Korea employed a sizeable administrative dataset of 352,245 individuals observed from 2009 to 2013 and found moderate changes in health-related behaviour after the diagnosis of T2DM [47]. The study's authors employed a regression discontinuity design method and compared how people immediate below and above the diagnostic cut-off value of 126 for fasting, plasma glucose behaved. They found a decrement of 0.96 centimetres (1.1% change) in waist circumference and a 0.158 kg/m$^2$ reduction in BMI (equivalent to 0.42 kg for a person with an average height of 163 cm)[4] among the group of people newly diagnosed with T2DM. However, these positive “gains” almost disappeared in the medium to long term (3 to 4 years after the time at which T2DM was detected), and they concluded, “knowing it is not half of the battle” because of the presence of this relapsing effect.

Several papers investigated behaviour change after the “health shock” of T2DM diagnosis using the US-based survey Health and Retirement Data (HRS) [49, 136, 137]. For example, a study by Slade, 2012 looked at the health trajectories of an intervention group of people newly diagnosed with T2DM compared to control group of individuals without new diagnosis but at risk of developing the condition as defined by a T2DM risk score algorithm developed by the authors of the study ( [49]. Their empirical investigation used all the nine waves of the HRS and non-linear dynamic population average probit models as estimation methods. They found significant changes in health-related behaviour among the participants recently informed of T2DM (intervention group) who curbed smoking by 1.5% (Std. errors 0,007, p-value <0.05) and decreased drinking activity by 8.5% (Std. errors 0.015, p-value <0.05) compared to the control group of

[4] 0.42 kg (=0.158*(1.63)2) for a person with the average height of 163 cm

individuals never diagnosed with T2DM but at risk of developing the condition. The authors also found an increased likelihood of starting frequent exercise by 4.2 % (Std errors 0.0025, p-value <0.05) but only among the most severe cases of T2DM i.e., those participants diagnosed with medication, a proxy for the severity of T2DM. Moreover, they also found evidence or recidivism since the effect vanished 2 years after diagnosis. In a similar way, also the probability of losing weight represented only a short shock for newly diagnosed patient who were about 4% (Std. errors 0.012; p-value <0.05) less likely to be overweight or obese at the time of diagnosis compared the control group of high-risk individuals. However, as it was the case for physical activity the maintenance of this positive effect it proved to be challenging for the newly diagnosed participants and disappeared within 2 years after they firstly reported their T2DM diagnosis.

Research by Keenan (2009) also exploited pooled longitudinal data from the HRS to determine smoking patterns and weight change consequent to the diagnosis of a series of chronic conditions, including T2DM [137]. The final sample counted 20,221 overweight or obese individuals and 7764 smokers followed for eight years, more specifically from the year 1992 to the year 2000. Her regression analysis highlighted that those individuals newly diagnosed with T2DM were 1.69 times more likely to quit smoking (95%CIs 1.08 to 2.65; p-value <0.001) and lost 0.6 more units of BMI (95% CIs -0.52 to -0.18; p<0.01; a decrease of ~ 1.7 Kg for a moderately active average middle-aged man[5]) than were individuals without a new diagnosis. In research conducted in 2012, Newson and colleagues exploited the same dataset. They increased the follow-up period by six years (1992–2006) to evaluate the long-term changes in smoking, exercise, and alcohol consumption

[5] The calculation was performed using the NHS BMI calculator for a moderately active (between 30 and 60 minutes a week) 60-year-old white male person (weight 80kg height 175cm).

on newly diagnosed individuals with T2DM, among other chronic conditions [136]. Their findings highlighted a 4.3% decrease in on the probability of an individual to be a current smoker (p-value <0.001) and a 1.8% decrease in alcohol consumption in people diagnosed with T2DM in the initial first two years after diagnosis. However, the study's authors concluded that the effect on alcohol arguably regarded a decline in occasionally excessive drinking rather than a reduction in daily consumption. There was also an 7% increase in the level of physical activity but only for the more educated diabetics participants. That being said, they also assessed a sequence of latent curve growth models to evaluate health trajectories for a period of up to twelve years. The models adjusted for gender, age, education, and functional limitations did not confirm the initial findings and showed no average long-term improvement in health behaviour following T2DM diagnosis.

A US-based study by Kahn (1999) analysed three cross-sectional datasets of the Nutritional Health and Nutrition Examination Survey (NHANES) for the years 1971–1994 to determine changes in healthy habits between a group of people recently diagnosed with T2DM and another group of people who met the diagnostic criteria for T2DM but never received a formal diagnosis [139]. This comparison allowed the net effect of the health information related to the diagnosis of T2DM to be disentangled since the two groups were almost identical, apart from the fact that the undiagnosed individuals were not aware of their condition. Predictions from their binary and Poisson count models supported the idea that people living with T2DM respond well to the “wake-up call” implied in the diagnosis of T2DM since they were less likely to smoke (16.2% diabetics ; 28% non-diagnosed diabetics; p-value <0.01) , and to consume alcohol (-0.84%; p-value <0.01) and more likely to exercise (-7%; p-value <0.01) compared to

their diabetics but undiagnosed counterpart after adjusting for age, gender, ethnicity and education. Conversely, another study from North America by Oster (2018) did not support these results [48]. The author used the Nielsen households level scanner data to evaluate variations in food purchasing after diagnosing T2DM and machine learning techniques. The diagnosis of T2DM was inferred based on purchases of glucose-testing products. The study detected a statistically significant reduction in the total number of calories purchased per household only in the initial first two months following the T2DM diagnosis (reducing unhealthy food purchases in particular). However, the consequences of this decreased unhealthy food purchase arguably translated only in a small reduction in weight (~0.22 to 0.45kg per month). Furthermore, these estimates were surrounded by a high degree of uncertainty due to inevitable methodological limitation. Another study from North America instead found a pre to post T2DM diagnosis increase in physical activity (+ 6%), a reduction in excessive alcohol consumption (- 5%), and smoking (- 3.4%) among the group of 478 participants who developed T2DM between wave 1 (1994) and the wave 7(2006) of the Canadian National Population Health Survey (NPHS) [135]. No significant changes were detected in the percentage of individuals who reported to eat at least 5 portions of fruit of vegetable daily after T2DM diagnosis. However, the average daily number of servings rose from 4.4 to 5.2 (p-value <0.01).

Nevertheless, research from Australia using population-level data from the New South Wales 45 and Up Study found no changes between baseline and follow-up in physical activity level nor fruit consumption for the T2DM group compared to the control group who did not report having diabetes [131]. Although they find that new diabetics were more likely to quit smoking (Odds ratio 2.71; 95% CIs 1.59 – 4.63; p-value <0.01) and lost a modest amount of weight 1.38 Kg [(–1.85

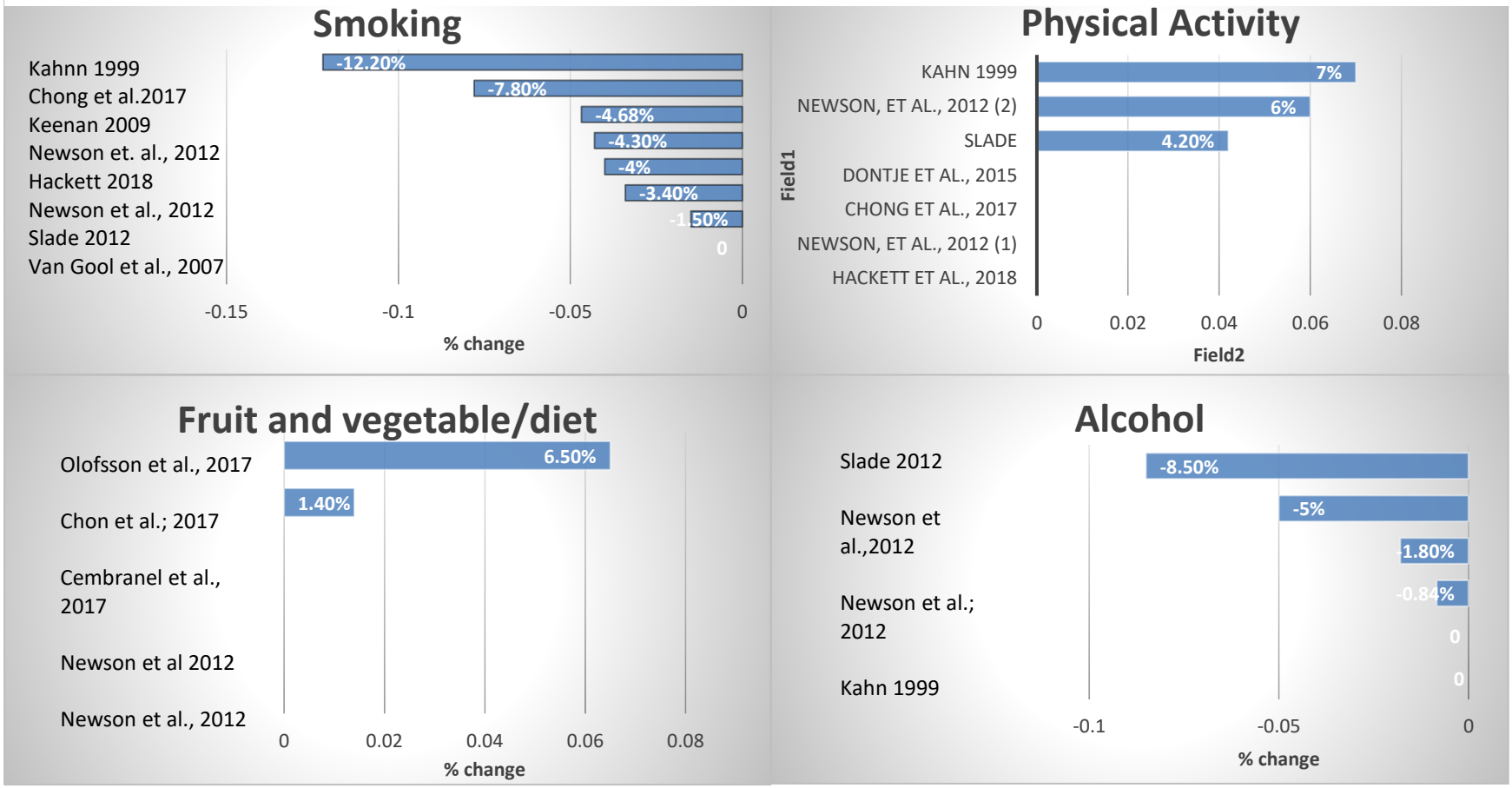
to –0.89); <0.0001]. Similarly, another study from Australia established that women recently diagnosed with T2M did not increase their physical activity levels [133]. Finally, a study from Brazil found minor changes in healthy food consumption apart from a decrease in fried food intake, and this effect was statistically significant in women only [132].

In summary, the literature on behaviour change following T2DM diagnosis is mixed [32, 45, 47, 49, 130-139] as summarized in figure 4.1 which reports effect sizes from the studies describes above expressed in percentages changes[6].

[6] Some of the studies already reported effect sizes in percentage changes (n=9). Results from other studies were reported in Odds Ratio and were converted (n = 2). For weight change the percentage change has been calculated using participants weight at baseline as the denominator (n=4).

**Figure 4-1 The effect of T2DM diagnosis on behaviour change**

**Figure 4.1 Effect of T2DM diagnosis on behaviour change.**



Some studies found decreased smoking [32, 49, 135, 137, 139] and alcohol consumption [135, 136, 139].However, other studies did not replicate these findings nor detected any significant change among these health behaviours between pre-and post-diagnosis [32, 140]. Equally, some studies found moderate improvements in the diet of people diagnosed with T2DM in terms of reduced overall calorie intake, decreased saturated fat consumption, and increased consumption of food rich in fibre content [47-49, 135]. In contrast, other research did not find any change in diet after the diagnosis of T2DM [32, 134]. The results for physical activity are even more mixed. Whereas some studies found improvement in physical activity level – i.e. increased odds of taking part in vigorous sport by the participants recently diagnosed with T2DM other research did not find any significant difference among this variable after the information of the diagnosis of T2DM [32, 49]. Only one study found significant changes in fruit and vegetable consumption, even if it must be noticed that this behaviour has been investigated in only three empirical analyses [32, 130, 136].

To conclude, overall, it is still unclear whether the health information of the diagnosis of T2DM can trigger behaviour change in newly diagnosed participants in observational studies and outside the context of a specific intervention designed to encourage a healthy lifestyle [27] [47-49]. There seems to be an overall theme which sees participants diagnosed with T2DM more likely to quit smoking. The effects size ranges from as little as 1.50% up to 12.20% and are always statistically significant at least at 5 per cent level. Although to a lesser extent, individuals recently diagnosed with T2DM appear to reduce alcohol consumption. However, changes in alcohol consumption appear to regard occasional episodes of excessive drinking rather than a steady decrease in daily alcohol intake. Minimal to moderate decrease in weight are also detected after

T2DM diagnosis with effects sizes in the range of -0.70% to -4 %. Nonetheless, these effects seem to be transient and did not persist in the medium to long term i.e., 2 or more years after T2DM diagnosis. Vegetable consumption and diet more in general as well as sedentary habits emerge as the most challenging behaviour to modify for the people recently diagnosed with T2DM.

This research will build upon Hackett et al. (2018) study and using the same dataset (ELSA) will address some of its limitations. First, I will use a different methodology, i.e., a random-intercept model, which will accommodate individual-level heterogeneity in response to T2DM diagnosis, a current gap in the literature that relies mainly on population-averaged effect. Second, I will use an additional methodology, e.g., propensity score matching - to minimise the bias due to observed confounders. Participants who will ultimately develop T2DM within the timeframe of the study might have different characteristics with respect to participants who did not develop the same condition. Therefore, if an effect of the T2DM diagnosis on behaviour change will be detected this may might be due to difference in observable characteristics between these two groups rather than a genuine effect caused by the T2DM diagnosis itself. By balancing out potential observables difference between the participants who stay T2DM free throughout the period covered by this study compared to participants who instead developed T2DM, will help to clarify whether and to what extent is extent the issue described above it will be representing a cause of concern.

The following section will describe the sample construction and methods for each of the three approaches employed in this analysis. Finally, the concluding section will compare the results for each of the methodologies used in this research to determine whether the findings are consistent among them.

### 4.1.3 Theoretical framework

As described in section 2.1.1, a distinctive feature of the Grossman framework is that individuals demand health for both consumption and investment reasons. The former refers to the fact that individuals, through consumption activities, may increase their immediate utility. The latter refers to the fact that the same individuals may also decide to reduce immediate consumption to increase their 'health stock'. This decision, in turn, in the long run, will increase their stock of time available for market and non-market activities. A natural implication arising from this dual aspect of the demand for health is a trade-off between behaviour that gives immediate gratification but worsens health outcomes in the long run and behaviour that demands efforts initially but improves health outcomes in the medium to long term [49]. Adhering to the recommended guidelines for type 2 diabetes requires costly adjusting behaviour by individuals to sacrifice current utility and invest in a healthier lifestyle (e.g., giving up smoking). The effort required to comply with these behaviours represents investments in health similarly as defined by Grossman. The original formulation of the Grossman model did not consider the impact of stochastic health shock, such as adverse health events [141]. Even its multiperiod version depends on age only. However, additional extensions of the model, by allowing the depreciation of health capital depend upon the level of health [142], suggest that negative exogenous health shock such as illnesses increases – at least from a theoretical point of view - the depreciation rate of health capital in a way similar to age [141]. Therefore, considering this theoretical outcome, it can be assumed that as of consequence of the T2DM diagnoses, individuals will invest more in their health by increasing health promotion activities [46]. In addition, the model also makes several predictions. First, considering that the health stock may depreciate faster as

people age (given a relatively inelastic demand curve for health), individuals would desire to offset this change by increasing the level of investment in their health as they age. Consequently, they will buy more medical goods, increase health activities, or both [143]. Second, since education increases the productivity of health investment, the model also predicts that the more educated individuals would demand a more extensive optimal stock of health. Third, people with high disposable income will invest more in their health than their lower disposable income counterparts. Many participants in the ELSA will be retired, and while part of them might have low incomes and rely on pension and benefits, others may have paid off their mortgages and have far more money to spend on their health. In addition, the following final hypothesis was added based on further extension of the Human Capital model that relaxed the assumption of the endogeneity of retirement in the household production function. Fourth, given that on retirement, people have more time to spend on non-market activities, e.g. more opportunity to exercise, they will invest more in their health [143]. Certainly, habits may have become embedded in a middle-aged population such as the one in the ELSA. However, leaving the workforce is a central transitional point in later life, which inevitably changes people's circumstances to give them more opportunities to increase health-protective behaviour [144]. Nevertheless, which one of these two contrasting effects might prevail, behaviour change remains a salient aspect for this age group. The prevalence of T2DM is far higher than in younger age groups and deserves further investigation [139, 145].

Sections 4.4 will describe the results to see whether these are in line with the theoretical prediction described above. In contrast, section 4.5 will summarize the main findings and discuss the practical implications of the result, especially in terms of policy recommendation and further opportunities for research. First, the

following section will expand upon the material and methods employed during work.

## 4.2 Methods

### 4.2.1 Data

This research uses data from the English Longitudinal Study of Ageing (ELSA), a representative longitudinal panel survey of community-dwelling older adults living in England aged fifty or more. The study commenced in 2002 (wave 1), with biennial follow up until 2016 (wave 8), the last available wave at the time of this research. The initial sample, which counts 11,391 participants, was drawn from households that responded to the Health Survey for England (HSE) in 1998, 1999, and 2001. Refreshment samples took place at waves 3, 4, and 6, making the number of participants per wave ranges between 9,000 to 11,000. The ELSA main questionnaire contains a wide range of socio-demographic and behavioural information. Furthermore, in addition to the main questionnaire, a nurse visit took place at every other wave starting from wave 2. A qualified nurse performed various anthropometric and biometric measurements during the visit, including a blood sample, which was subsequently sent to a laboratory for analysis. All this biometrics information is available in a dedicated module of ELSA, namely the nurse visit.

### 4.2.2 Empirical strategy

The empirical strategy consists of three distinct methods. The first method (Model 1) will replicate, as closely as it is practical, the analysis performed by Hackett et al., 2018 in their recent longitudinal analysis on behaviour change after T2DM diagnosis [32]. Therefore, Generalized Estimating Equations (GEE) models, the same method applied by Hackett et al., will be implemented and described in

section 4.3.1.1. The second method, a random intercept logit model (Model 2), is introduced in the section below 4.3.1.2 which by including a subject specific random intercept ζj into the model will allow for the calculation of subject specific effects as opposed to population average effects as it is the case for the GEE estimation method describe above [146] [129]. This is a crucial aspect because it will allow to incorporate individual level heterogeneity into the model in a more thorough way. As briefly described before, there might be time-invariant individual-level unobserved characteristics related both to the probability of developing T2DM and to the probability of changing behaviour. Consequently, between-subjects comparisons are susceptible to unmeasured confounding. As extensively documented in chapter 2, there is an overwhelming body of evidence which links time and risk preference to each of the outcomes of interest of the present analysis: smoking, alcohol consumption, physical activity, and fruit and vegetable consumption [20, 21, 39, 63]. Furthermore, preferences are also related to the probability of developing T2DM because individuals who are less likely to engage in healthy behaviour are also more likely to develop diabetes [147]. Therefore, not incorporating individual-level heterogeneity will result in omitted variables bias, leading to biased estimates and inefficient standard error. On the other hand, the introduction of individual level random effects will pick up the effect of these time-invariant characteristics between individuals and therefore it will address the problem caused by omitted variable bias (OVB). This will be achieved by breaking the correlation between the individual level random effect, the individual specific error term, and the included explanatory variables.

Participants who develop T2DM may have different characteristics from those who do not develop the same condition. Therefore, to conclude the section about the methods, a Propensity Score Matching (PSM) approach [148] (Model 3) will

be discussed in 4.3.1.3. More in detail, a control group of participants who never self-reported a diagnosis of T2DM between baseline (wave 3) and the latest available follow-up (the wave 7) will be constructed and matched to a treatment group of participants diagnosed with T2DM over the same period on a range of sociodemographic variables. The PSM model will account for potential confounding effects and provide a more statistically efficient, e.g. more robust solution over regression techniques that adjust for a number of confounders [149]. However, it assumes that all variables that affect treatment assignment and outcome have been measured, e.g. 'no unmeasured confounders' [150]

Therefore, using PSM and the regression approaches described before to answer the same research question will provide additional robustness to the results. For example, it will determine if the results of the three methods are concordant or discordant. The a priori expectation is that both regression adjustments and PSM should give similar results [151]. A comparison of the results obtained with these three approaches will be examined in section 5, the final discussion.

More specifically, I proceeded to estimate the following model, which will be consistent across all three approaches, i.e., GEE, RE and PSM:

$$Logit\{\Pr(yij = 1|xij, \varsigma j)\} = \beta 1 + \beta 2x2j + \beta 3x3j + \beta 4x4j + \beta 5x5j + \beta 6x6i + \beta 7(x5j * x6i) + \varsigma j + \varepsilon ij$$

Where $yij$ is the outcome y for the subject *j* at occasion *i conditional* on a set of covariates measured at baseline $x2j, x3j, x4j$ i.e., age, gender, and non-pension wealth and the cluster-specific (in this case individual-specific) random intercept $\varsigma j$. The equation also specifies the group effect $x5j$ i.e., the effect of the group independent of time which in this case is represented by a dummy variable for

subject j indicating whether that individual has been diagnosed with t2dm during the study period (1: diagnosed with T2DM; 0 never diagnosed). The equation also specifies a time effect $x6i$ (divided into pre-diagnosis period T0, peri-diagnosis period T1 and post-diagnosis period T2), representing the effect of time independent of group, and the time by group interaction $x5j * x6i$. This latter effect is of the utmost interest since it compares the change in outcomes, i.e., health behaviour between the groups over time. Therefore, it will indicate whether the T2DM diagnosis leads to a greater change in outcomes in the intervention group compared to the control.

From 4.2.3 to 4.4.5, the following subsections will describe the outcomes, exposures and covariates, and the construction of the samples employed in each different type of analysis, e.g. GEE, RE and PSM, respectively.

### 4.2.3 Outcomes: health behaviours

Five distinct health behaviour represent the outcomes of the current analysis. These outcomes include smoking status, alcohol consumption, physical activity, sedentary behaviour and fruit and vegetable intake. The outcomes variables are the same regardless of the model.

Smoking status was assessed with an indicator (yes/no) that originated entirely from the item: *"Do you smoke cigarettes at all nowadays"*—respondents who reported smoking were classified as *current smokers* and as *non-smokers* otherwise.

Alcohol consumption was measured using the item that asked participants: *"On how many days out of the last seven did you have an alcoholic drink?"*. Based on the answer to this question, a binary indicator (yes/no) was constructed,

categorising respondents as *daily drinkers* if they reported drinking from 5 to 7 days a week and as *non-daily drinkers* otherwise.

Physical activity levels were measured with a question that examines how often participants engaged in any kind of physical activity. This could have been of moderate/mild intensity - e.g., brisk walking – or vigorous exercise, e.g., running, playing tennis or structured exercise at the gym. In more detail, the main questionnaire contains an entry where respondents were asked: *"Do you take part in any sports that are vigorous, moderate or mildly energetic?"*. The possible answers to this question involved four possible options, more precisely: "*more than once a week; once a week; one to three times a month; hardly ever or never*". According to this item, respondents were classified as *"active"* if they mentioned practising physical activity at least once a week and as *"non-active"* otherwise.

The construction of the sedentary behaviour binary (yes/no) indicator followed a similar approach to the abovementioned one. It was entirely based on the same item used to construct the variable for physical activity levels; however, the possible responses were coded differently in this case. Respondents were classified as *sedentary* if they reported frequencies such as *hardly ever or never* and *non-sedentary* if they stated a frequency higher than this.

Fruit and vegetable consumption was measured using three different items. During waves 3 and 4, respectively, the following items were used*: "How many slices of large fruits such as melons did you eat yesterday"* and *"How many cereal bowlfuls of salad have you had yesterday?"*. Starting from wave five instead, a specific item interrogates participants about their fruits and vegetable consumption with the question*: "How many portions of the fruit or vegetables do*

*you eat on a given day?"*. These three different items were combined to construct an indicator (yes or no) that describes participants who consume at least five portions of fruit and vegetables daily.

### 4.2.4 Exposure and covariates

Similarly, to the outcome variables, the exposure and covariates are the same regardless of the methodology employed, e.g., the same for each model. Predictors include age (expressed in years and regarded as a continuous variable), sex (categorised as either male or female), education (divided into the category of no qualification, high school certificate or A-level, and college degree) and fifths (1 = low, 5 = high) of non-pension wealth as a measure for income. All these characteristics were retrieved from the ELSA main questionnaires. Non-pension wealth is the measure for income adopted by Hackett and colleagues. Therefore, given this analysis's replicative nature, I also adopted non-pension wealth as a measure for income.

The variable for education was obtained from the wave 5 main questionnaire. That relies on the fact that educational attainments were only evaluated at the wave 5 and updated at consequent waves only if new qualifications had been recently awarded to the participants. There was missing information about this variable, but they counted for less than 5% of the cases and were not deemed a cause of great concern. Furthermore, since the sample is predominantly middle-aged, very few participants (less than 1%) had updates for this variable.

The following two variables, namely CASP-19, a measure for quality of life measured on a scale from 0 to 57 where higher score indicates better quality of life and HbA1c (%), were used only to test differences at baseline between T2DM and control group and were not included in any of the models also in

consideration of the fact that they might be potentially endogenous and thus representing a possible source of bias. Body Mass Index (BMI), defined as weight in (kg)/height ($m^2$) was used to test differences at baseline between T2DM and control group but it has also been included in the sensitivity analysis for the GEE model. BMI and HbA1c are not available in ELSA's main questionnaire and therefore were retrieved from the nurse module during wave 2. CASP-19 was retrieved from the main questionnaire instead. It is worth recalling here that the wave 2 nurse module was chosen as the source of information for these variables because it is the closest in time to the baseline point of the analysis represented by wave 3. It is worth noting that the baseline point is also the same regardless of the model. Finally, data on the proportion of respondents who self-reported limited long-standing illness, stroke, coronary heart disease or any of the seven CVD related disease (angina, heart attack, congestive heart failure, heart murmur, abnormal heart rhythm, stroke, and other heart disease) were all retrieved from the ELSA main questionnaire. All these variables were used only to test difference baseline between the T2DM and comparison group, apart limiting long standing illnesses which was also employed in the last sensitivity analysis of the GEE model only.

The variable general health which has only been used in the PSM approach was retrieved from an item included in the ELSA which asked respondents to report their general health on a scale from 1 to 5 (1= excellent, 2 =very good, 3 = good, 4 = fair, 5 = poor or very poor).

The self-reported diagnosis of T2DM represents exposure as consistently recorded in each wave of the main questionnaire. This variable was retrieved from the item which asked respondents: *'Have you ever been diagnosed with diabetes or high blood-sugar reading? (yes/no)'.*

### 4.2.5 Construction of the samples

#### 4.2.5.1 Generalised Estimating Equations study sample.

The Generalised Estimating Equation (GEE) analysis replicates as closely as practical the analysis performed by Hackett et al., 2018. Therefore, the construction of the final sample for the GEE analysis will follow step by step the procedure adopted by Hackett and colleagues in their recent publication on behaviour change after the diagnosis of T2DM figure 4.1. According to this approach, a total of 16,090 respondents free of diabetes at wave 3, the baseline point of the current analysis, were included in the study. Since fruit and vegetable consumption data were only available starting from wave 3, the 917 participants diagnosed with diabetes up to wave three were excluded from the final sample. In addition, also the 248 participants diagnosed with diabetes at wave 7 were excluded from the study because of a lack of follow-up data. Again, this is because wave 8 was not available at the analysis performed by Hackett and colleagues.

Finally, according to the approach adopted by Hackett et al.,2018 only participants with spells of data for three consecutive waves for at least one health-related behaviour were included in the final sample, resulting in 5454 participants being excluded from the analysis. The final sample counts 9453 unique individuals. Among these participants, 5764 had data on smoking, 4356 had information on alcohol consumption, 7532 reported their fruit and vegetable intake, 7855 conveyed data about sedentary behaviour, and 7855 specified their physical activity habits.

Subsequently, following the same approach as Hackett et al., 2018, this final sample was split into two groups, a comparison and T2DM groups respectively. The T2DM group comprises participants diagnosed with T2DM, either at wave 4,

wave 5, or 6. The number of participants diagnosed during each wave was 127 for wave 4, 206 for wave 5 and 164 for wave 6: in total, 497 individuals were diagnosed with T2DM up to wave 6. The comparison group involved participants who never self-reported a diagnosis of T2DM throughout the whole period covered by this study. This group counts 8438 unique individuals.

Overall, the existing analysis makes use of three different time points. For the T2DM group, these three-time points are represented by the wave preceding the diagnosis, called the pre-diagnosis period (T0). The wave in which the T2DM diagnosis was first reported, called the peri-diagnosis period (T1). Finally, the wave after the one in which the T2DM diagnosis was first reported represents the post-diagnosis period (T2). Therefore, the pre-diagnosis period for the T2DM group could be either wave 3, 4 or 5; the diagnosis period can occur at any wave between wave 4 and wave 6. The post-diagnosis period can be exemplified by waves 5, 6 or 7. Given the available information from the Hackett et al., 2018 paper, for the comparison group, T0, T1 and T2 instead were represented by the waves 4, 5 and 6, respectively.

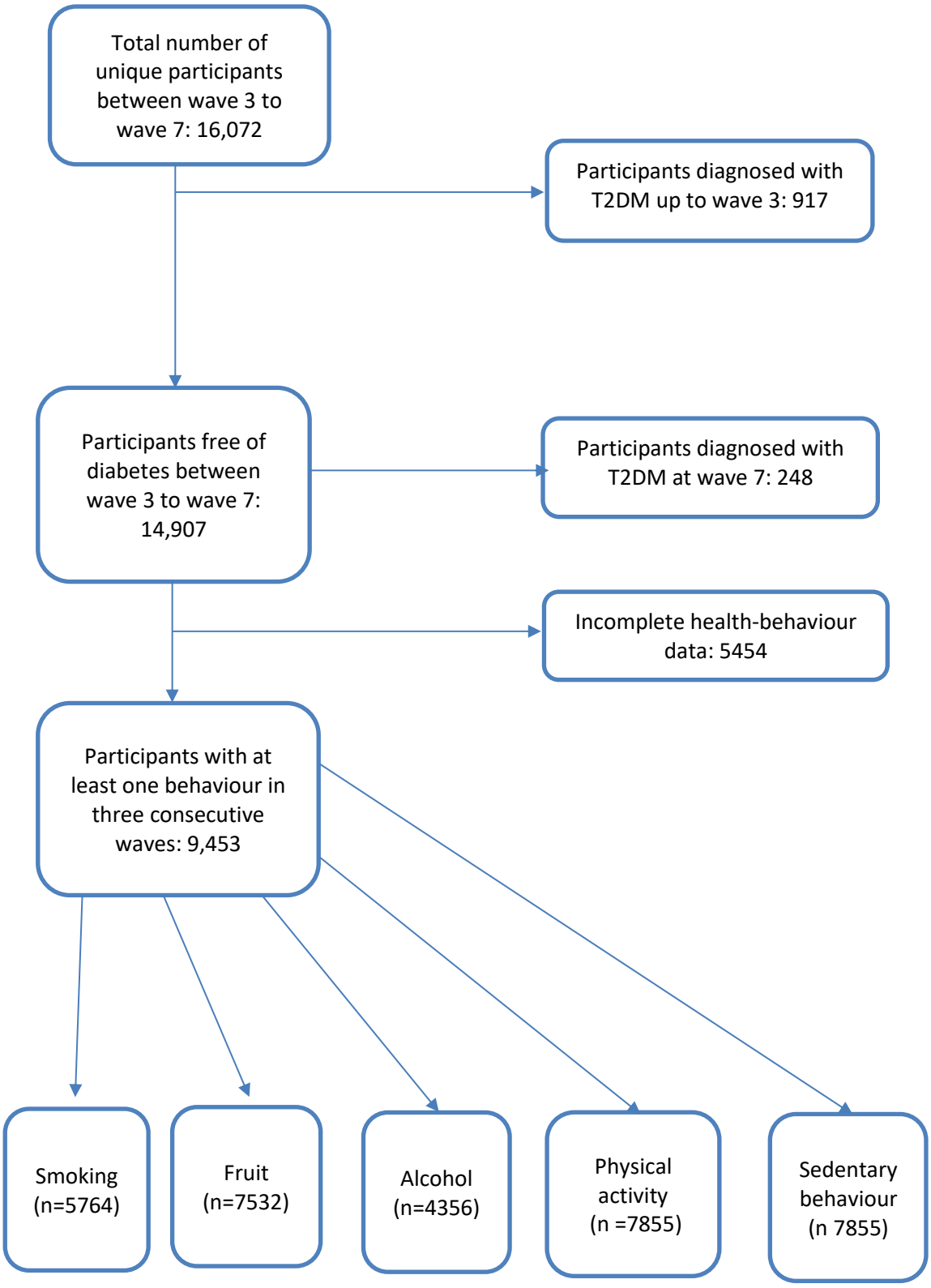



**Figure 4-2 Flow diagram of participants included in the final sample. The waves 3, 4, 5, and 6 were merged to obtain the total participants. Only participants free of diabetes at wave three and for which at least one behaviour for three consecutive waves was available were included in the final sample.**

There were no duplicates in the final sample, i.e., the combination of participants personal identification code coupled with the time variable (wave) uniquely identified each participant.

#### 4.2.5.2 The random effect study sample

The random effect study sample is the same as the sample used in the GEE analysis. However, it is worth recalling here that only for exploratory purposes – i.e., to test for possible differences at the baseline – an additional descriptive analysis was performed with respect to Hackett et al., 2018 as indicated in section 4.3.1.2 with more detail. While Hackett et al., compared in terms of descriptive characteristics a T2DM group of participants who developed T2DM between the wave 3 and 7 to a control group of participants never diagnosed with T2DM throughout the whole period covered by the study, we included an additional control group. This additional control group include participants who reported a diagnosis of T2DM at wave three or earlier. This second control group has been temporary included in the sample only for descriptive purposes and it is not part of the RE regression sample. This group has been labelled "*early diagnosed*" (ED) to distinguish it from the group of *later diagnosed* participants (LD), e.g., participants who self-reported a T2DM diagnosis starting from wave 3 onwards. The addition of a second control group will advance the exploratory analysis of Hackett and colleagues by allowing the possibility to test for potential differences at baseline between these three groups, e.g., the group of people who received a diagnosis earlier (before the wave three) may have different characteristics compared to the group of people newly diagnosed with T2DM section 4.4.2. Despite being of interest, however, it must be acknowledged that it represents a small control group by definition.

#### 4.2.5.3 Propensity Score Matching study sample.

A control group of participants never diagnosed with T2DM was matched on a series of sociodemographic characteristics to a treatment group of participants who received a diagnosis of T2DM during the period covered by the study on 4:1 ratio. This resulted in final sample of 924 unique participants. More detailed information about how treatment and control groups have been constructed will be provided in the statistical analysis section 4.3.1.3.

## 4.3 Statistical analysis

Longitudinal data structures, like the one analysed in the current empirical investigation, where the responses from the same participant (unit) are recorded at different waves (occasions) are clustered by definition and require appropriate treatment in order to achieve satisfactory inference. This is because, in a longitudinal context such as the one described above, it is unrealistic to assume that the responses for a given participants are conditionally independent given the covariates e.g., the errors terms are independent. There might be individual level omitted characteristics that are correlated with the treatment, in this specific context represented by the T2DM diagnosis, which will introduce bias to the point estimates. GEE (Model 1) overcome this obstacle by assuming a working correlation between these different occasions within the same cluster (subject). Therefore, it represents a convenient general approach to model responses from the same subject over time. GEE reflects population averaged effects which might be different from subject specific effects, therefore the decisions to implement a RE effect approach (model 2) as described in the section 4.1.1 about the objectives. Finally, as briefly recalled 4.2.2 people who develop T2DM might have different characteristics from people who do not develop the same

condition. Consequently, a PSM approach (model 3) will also be implemented in section 4.3.1.3 to adjust for confounders.

The following sub-sections will expand upon how each of these models described above has been developed.

#### 4.3.1.1 Generalized Estimating Equations model (Model 1)

Pre-diagnosis characteristics between the T2DM and control groups were compared using the Mann-Whitney U test, Pearson's chi-squared test and paired t-tests. In particular, the Mann-Whitney U test was utilised to compare the medians for the variable age. Pearson's Chi-squared tests were used to test for any statistically significant difference among the T2DM group and control group for the categorical variables sex, wealth, education, limiting long-standing illness and cardiovascular diseases. The t-tests were implemented to assess the equality of the means between the two groups for the variables Body Mass Index (BMI) and Blood Glycated Haemoglobin (HbA1c). Movement across different categories for each of the five health-related behaviour was compared using Mc-Nemar's test. This test was run for each group separately. Population-averaged panel data models were fitted using Generalized Estimating Equation (GEE) regression methods with an exchangeable correlation matrix. All the analysis was performed using the statistical package Stata version 15.1.

#### 4.3.1.2 Random Effects Logit Model (Model 2)

Similarly, to the approach adopted for the GEE analysis, characteristics - e.g., age, sex, BMI at pre-diagnosis between the T2DM group and control group were compared using the Mann-Whitney U test, Pearson's chi-squared test and paired t-tests, respectively. Likewise, differences for each of the five health behaviours included in the analysis at the post-diagnosis period between the control and

T2DM groups were evaluated using the Mc-Nemar's test. An additional control group of people who had already reported a diagnosis of T2DM by wave 3 (baseline point) were added to the comparison. Therefore, the T2DM group will be compared against two different control groups. Newly diagnosed diabetic patients populate the former control group, as was the case for Hackett et al. (2018). The latter control group will be represented by people already diagnosed with T2DM at the starting point of the analysis (wave 3).

In summary, this exploratory analysis will benefit from a different comparison group of participants e.g., people already diagnosed with T2DM, with a more extended duration of T2DM that may have different health behaviours concerning both the newly diagnosed and never diagnosed participants.

The RE analysis will be performed using logistic regressions models with an individual-level random intercept ϛj as previously described in more detail in section 4.4. In addition, the estimation will be performed by maximum-likelihood using the Gauss-Hermite quadrature and twelve integrations points instead of the ten used by default in Stata [129].

#### 4.3.1.3 Propensity score matching (Model 3)

The PSM approach entails forming two groups of treated and untreated individuals who share similar propensity scores [148]. In the context of the current empirical investigation, the treatment is the self-reported diagnosis of T2DM, whereas each of the five-health behaviour represents the outcomes (please refer to section 4.2.4). Therefore, according to this approach, a treated group (intervention group) of participants who ultimately received a diagnosis of T2DM between wave 3 and wave 7 will be matched to an untreated group (control group) of participants who never received such diagnosis over the same period,

based on a set of observable characteristics. In this case, these observable characteristics are described in section 4.2.4 and include age, sex, income and general health. A one to four matching, e.g., each participant in the T2DM group was matched to 4 participants in the control group – was performed using the nearest neighbourhood algorithm with a calliper distance of 0.2 which is argued to be sufficient to reduce bias arising from unmeasured confounders. Propensity scores, e.g. the probability of treatment assignment conditional on observed baseline covariates, will be calculated using logistic regression [150].

The treatment effect was calculated using random effect logistic regression on the matched sample following the exact model specification and the same covariates as of the GEE and RE approach e.g., general health was used only in the matching and was not included in the RE model on the matched sample.

## 4.4 Results

This section about the results is organized as follows: sections 4.4.1 and 4.4.2 will report descriptive characteristics for the GEE and RE sample, respectively. It is essential to acknowledge that this is an exploratory analysis; thus, formal hypothesis testing is limited due to the effect of potential confounders.

From 4.4.3 to section 4.4.7, the following sections will present results for each health of the five-health behaviour studied in this analysis, which is worth recalling for clarity reasons are:

I. Smoking
II. Alcohol
III. Physical Activity
IV. Sedentary Behaviour
V. Fruit and Vegetable Consumption.

Results for each of these five health behaviours reported above have been subsequently divided further into three subsections according to methods employed during the analysis, e.g., GEE (model 1), RE (model 2), PSM (model 3). For example, section 4.4.3, which reports the results for smoking, has been divided into subsections 4.4.3.1, 4.4.3.2, and 4.4.3.3, respectively. Each of these subsections presents the result for smoking for each model. Therefore section 4.4.3.1 will present the results for smoking according to the GEE analysis (model1), section 4.4.3.2 will present results according to the RE analysis (model 2), and to conclude, subsection 4.4.3.3 will describe results for the PSM analysis (Model 3). This procedure has been applied to each of the five health behaviours studied in this research.

For coherence with Hackett et al., 2018 research findings from the GEE will be presented both within a table as well as graphically i.e., the average marginal effect predictions at the means from the coefficients (betas) of the fitted GEE models. Furthermore, results from the RE analysis will present the regression outputs from the Random Effect Logit model in terms of beta coefficients. Finally, the PSM analysis will also report the results in terms of beta coefficient as the previous GEE and RE approach. Results in the form of odds ratios for the GEE and RE model will be presented in the Appendix C1. Coefficients from the RE model are expected to be of greater magnitude.

### 4.4.1 Descriptive characteristics for the Generalized Estimating Equation sample

The comparison of the characteristics at pre-diagnosis (T0) between the T2DM group and control group, as reported in table 4.1, shows that it is not possible to accept the null hypothesis of the equality of the medians between the two groups for the variable age (p-value < 0.01). This suggests that participants diagnosed

with T2DM were significantly older on average (65 years the median age in the T2DM group vs 63 years in the control group). Similarly, the results revealed significant differences between the T2DM and control group for sex, non-pension wealth and education. People who reported a diagnosis of T2DM were more likely to be male (p-value < 0.001), less educated (p-value < 0.001) and from a lower-wealth quintile (p-value < 0.001). The proportion between males and females in the T2DM group was almost equally split, whereas, in the control group, there was a lower percentage of males (51.35% in the T2DM group vs 43.5% in the control group). The percentage of participants with a college degree was greater in the comparison group (11.43% in the T2DM group vs 20.07% in the control group) as well as the share of respondents from the lowest wealth quintile was more pronounced in the T2DM group with respect to the group of participants never diagnosed with diabetes (26.67% in the T2DM vs 15.75% in the control group). Outputs from Pearson chi-squared tests also highlight a statistically significant relationship among the two groups in the frequency of reporting long-standing illness. Participants diagnosed with diabetes were more prone to report limiting long-standing conditions (46.80% in the T2DM group vs 31.37% in the control group, p-value 0.006). Similarly, people who reported a diagnosis of T2DM were more likely to experience cardiovascular diseases (31.53% in the T2DM group vs 28.06% in the control group, p-value <0.001) compared to their counterparts of people who never reported a diagnosis of T2DM. Paired t-tests rejected the null hypothesis of the equality of the means between the two groups for HbA1c and BMI. This suggests statistically significant differences in the means for these two variables among people who reported a diagnosis of T2DM compared to people who did not report such a diagnosis. Participants from the T2DM group, had on average a higher BMI (31.53 vs 28.06 $m^2$/kg, p-value <

0.001) and a higher HbA1c percentage (6.77% vs 5.79%, p-value 0.001) These values indicate vast differences between the two groups, which is the rationale behind the PSM approach. Given these differences at baseline even if an effect of T2DM diagnosis would be detected, it would be difficult to attribute this effect to the T2DM diagnosis rather than to differences in prognostic factors between the T2DM and control group such as BMI and HbA1c. In particular, the average value for HbAc1 of 6.77% in the T2DM group is of great importance because it is above the cut-off value of 6.5% for T2DM diagnosis. This indicates that a significant proportion of the participants in the T2DM group had already developed T2DM but was still undiagnosed.

**Table 4-1 Comparisons of participants' characteristics at the pre-diagnosis period (T0). Significance level p-value <0.05**

| | N | Diabetes group Median (IQR) | N | Control group Median (IQR) | P-value (T2DM vs control) |
|---|---|---|---|---|---|
| Age | 497 | 65(9.75) | 8,438 | 63(10.07) | <0.001 |
| | | N (%) | | N (%) | |
| Sex, men | 497 | 255 (51.35%) | 8,438 | 3,666(43.45%) | <0.001 |
| | | | | | |
| Wealth categories (%) | 435 | | 7,428 | | <0.001 |
| 1(lowest) | 116 | 26.67 | 1,170 | 15.75 | |
| 2 | 106 | 24.37 | 1,404 | 18.90 | |
| 3 | 92 | 21.15 | 1,488 | 20.03 | |
| 4 | 62 | 14.25 | 1,621 | 21.82 | |
| 5 | 59 | 13.56 | 1,745 | 23.49 | |
| | | | | | |
| Education (%) | 490 | | 8,231 | | <0.001 |
| No qualification | 172 | 35.10 | 2,059 | 25.07 | |
| High school certificate | 262 | 53.47 | 4,506 | 54.86 | |
| College degree | 56 | 11.43 | 1,648 | 20.07 | |
| | | | | | |
| Limiting long standing illness (%, yes) | 497 | 230 (46.80%) | 8,438 | 2,500(31.37%) | 0.006 |
| | | | | | |
| Cancer | 207 | 14(6.67) | 8438 | 648(6.42) | 0.554 |
| Coronary heart disease | 207 | 32(15.46%) | 8438 | 764(9.05) | <0.001 |
| Stroke | 207 | 19(9.18%) | 8,438 | 326(3.86%) | <0.001 |
| Cardiovascular disease (% yes) | 497 | 130 (26.16%) | 8,438 | 1,854 (20.56%) | 0.0029 |
| | | Mean (SD) | | Mean (SD) | |
| BMI | 384 | 31.53 (6.42) | 6,727 | 28.06 (5.098) | <0.001 |
| HbA1c | 280 | 6.77 (1.10) | 5,279 | 5.79 (0.56) | <0.001 |
| CASP19 | 388 | 39.38(9.27) | 7050 | 41.75(8.40) | <0.001 |

Changes in the proportions of participants in each of the five health-related behaviour between pre- and post-diagnosis periods are presented in table 4.2. There was a decrease in the percentage of participants who reported smoking among both the T2DM and comparison group respectively between T0 and T2 (23.61% vs 17.71%, p-value <0.001 in T2DM group; 21.95% vs 18.38% p-value <0.001 in the control group) which it can be speculated to reflect just a general decline in smoking in the general population over the past few decades, at least in England and in most western countries. An increase in the fraction of people diagnosed with T2DM who reported sedentary behaviour was also detected between T0 and T2 (76.08% vs 82.69%, p-value 0.001). Conversely, a slight decrease in the proportion of people who regularly engaged in vigorous or mild exercise was also detected (7.74% vs 6.38%, p-value < 0.001). A moderate reduction in vegetable consumption was found among people living with T2DM between the pre and post-diagnosis periods (8.01% vs 6.07%, p-value < 0.001).

Regarding the control group of people never diagnosed with T2DM throughout the whole period covered by this study, a slight decrease in fruit and vegetables between T0 and T2 was distinguished (7.73% vs 6.46 %, p-value 0.001). A more substantial decrease between pre- and post-diagnosis periods for this group was found in the proportion of people who reported to be current smokers (29.95% vs 18.13%, p-value 0.001), whereas the proportion of individuals who reported to drink alcohol daily (39.43% vs 39.35%, p-value < 0.001) remains stable over time. To conclude, an increase in sedentary behaviour (58.53% vs 62%, p-value 0.001) was also detected among the control group.

| | Diabetes group | | | | Control group | | | |
|---|---|---|---|---|---|---|---|---|
| Health Behaviour | N | T0 | T2 | P value (T0 vs T2) | N | T0 | T2 | P value (T0 vs T2) |
| Smoking (% yes) | 288 | 68(23.61%) | 51 (17.71%) | <0.001 | 4,771 | 1,407 (21.95%) | 877 (18.38%) | <0.001 |
| Alcohol (% daily) | 134 | 41 (30.06 %) | 44 (32.80 %) | <0.001 | 3,551 | 1,400 (39.43) | 1,402 (39.35%) | <0.001 |
| Physical activity (% active) | 439 | 34(7.74%) | 28 (6.38%) | <0.001 | 7,834 | 1400(17.87%) | 1,369 (17.48%) | <0.001 |
| Sedentary (% yes) | 439 | 334 (76.08%) | 363 (82.69%) | <0.001 | 7,843 | 4,585 (58.53%) | 4,857 (62%) | <0.001 |
| ≥5 portions fruit & vegetables daily (% yes) | 312 | 25 (8.01%) | 192 (6.07%) | <0.001 | 6,130 | 474(7.73%) | 396 (6.46%) | <0.001 |

**Table 4-2 Movements in the proportions of participants engaged in each health behaviour between pre-diagnosis (T0) and post-diagnosis period (T2) among both the diabetes group and control group. Descriptive characteristics for the Random Effect sample. Significance level p-value <0.05**

### 4.4.2 Descriptive characteristics RE sample

Table 4.3 compares the intervention group of participants newly diagnosed with T2DM – i.e., participants diagnosed at any time between wave 4 and wave 7 – which has been named *"later diagnosed"* (LD) against two different control groups. The former of these control groups will be the 'usual' control group of people never diagnosed with T2DM. In contrast, the latter will be represented by participants who reported a T2DM diagnosis at wave 3 (baseline) or before named *"early diagnosed*" (ED).

A comparison of the participant's characteristics at baseline (wave 3) revealed differences between the intervention group of participants newly diagnosed with T2DM (LD-T2DM) - i.e. people diagnosed at any time between wave 4 and wave

7- and the control group of individuals diagnosed with T2DM before wave 3 (ED-T2DM) in terms of lower prevalence of cardiovascular diseases (26.16% vs 20.56%, p-value <0.001) and lower hba1c percentage (6.77% vs 7.12 %, p-value <0.001) for the N-T2DM group. No other statistically significance difference was found among these two groups in terms of baseline characteristics.

| | N | L T2MD group Median (IQR) | N | E T2DM | N | Control group Median (IQR) | P-value (T2DM vs control) | P value (N T2DM vs E T2DM) |
|---|---|---|---|---|---|---|---|---|
| Age | 497 | 65(9.75) | 572 | 67.5(14) | 8,438 | 63(10.07) | <0.001 | 0.057 |
| | | N (%) | | N (%) | | N (%) | | |
| Sex, men | 497 | 255 (51.35%) | 572(53.67) | | 8,438 | 3,666(43.45%) | <0.001 | 0.440 |
| | | | | | | | | |
| Wealth categories (%) | 435 | | 551 | | 7,428 | | <0.001 | 0.316 |
| 1(lowest) | 116 | 26.67 | 148 | 26.86 | 1,170 | 15.75 | | |
| 2 | 106 | 24.37 | 107 | 19.42 | 1,404 | 18.90 | | |
| 3 | 92 | 21.15 | 120 | 21.78 | 1,488 | 20.03 | | |
| 4 | 62 | 14.25 | 98 | 17.79 | 1,621 | 21.82 | | |
| 5 | 59 | 13.56 | 78 | 14.16 | 1,745 | 23.49 | | |
| | | | | | | | | |
| Education (%) | 490 | | 572 | | 8,231 | | <0.001 | 0.608 |
| No qualification | 172 | 35.10 | 196 | 34.27 | 2,059 | 25.07 | | |
| High school certificate | 262 | 53.47 | 299 | 52.27 | 4,506 | 54.86 | | |
| College degree | 56 | 11.43 | 77 | 13.46 | 1,648 | 20.07 | | |
| | | | | | | | | |
| Limiting long standing illness (%, yes) | 354 | 230 (64.97%) | 467 | 302(64.66) | 4,382 | 2,500(61.16%) | 0.006 | 0.103 |
| | | | | | | | | |
| Cardiovascular disease (% yes) | 497 | 130 (26.16%) | 522 | 196(37.55) | 8,438 | 1,854 (20.56%) | 0.0029 | <0.001 |
| | | Mean (SD) | | | | Mean (SD) | | |
| BMI | 384 | 31.53 (6.42) | 537 | 30.90(6.17) | 6,727 | 28.06 (5.098) | <0.001 | 0.088 |
| HbA1c | 280 | 6.77 (1.10) | 360 | 7.12(1.65) | 5,279 | 5.79 (0.56) | <0.001 | 0.025 |
| CASP19 | 388 | 39.38(9.07) | 468 | 39.06 | 7050 | 41.75(8.04) | <0.001 | 0.613 |

**Table 4-3 - Comparisons of participants' characteristics at the pre-diagnosis period (T0)**

### 4.4.3 Descriptive characteristics PSM sample

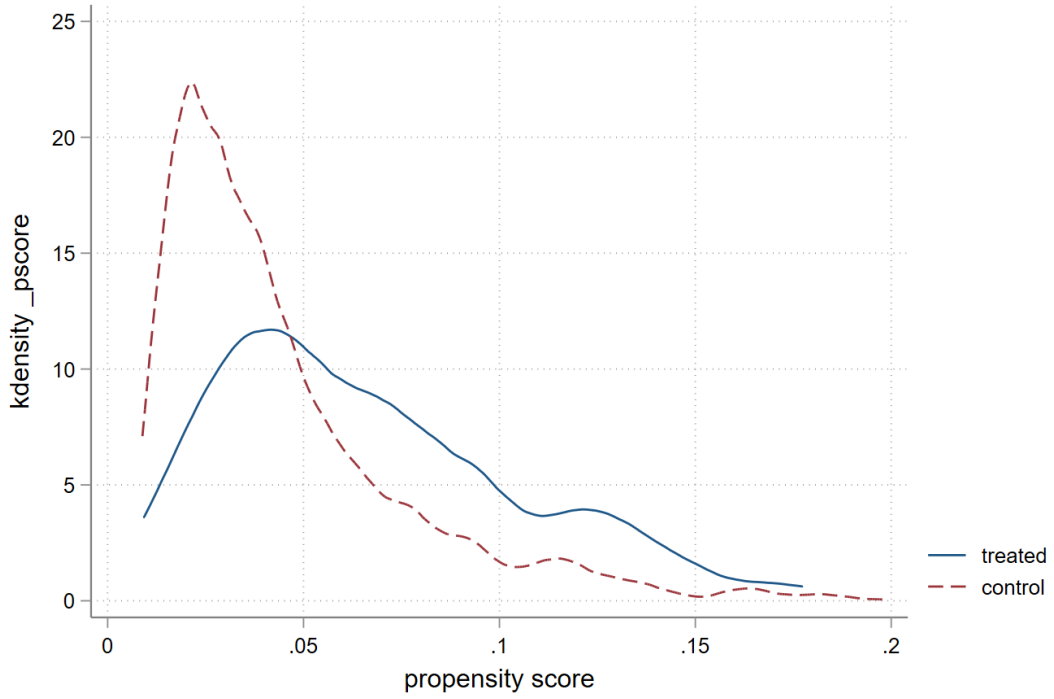
Descriptive statistics for the post matching sample are reported in table 4.4, which indicates that the two groups (T2DM and control) are more comparable post-matching in terms of the observable characteristics at baseline. T-tests and chi-squared tests comparing the characteristics between the two groups became all non-significant after the matching. The mean age in the pre matching sample was 66.01 years in the control group and 67.48 years in the T2DM group respectively, with an age difference of 1.47 years between the groups before the PSM was implemented. This difference levelled at 0.13 years in the post-matching sample. Similarly, the distribution of non-pension wealth differed substantially; before the matching, only 12.37% per cent of the T2DM group pertained to the highest wealth quintile compared to 22.95% of the control group. However, these differences flattened considerably after the matching, and the proportions of participants belonging to the highest non-pension wealth quintile were almost identical in the post-matching sample (12.37% in the control group vs 12.99% in the T2DM group). The T2DM and control group appeared very different in terms of general health at baseline. For instance, in the pre matching sample, there was a much higher proportion of participants who self-reported poor general health at baseline in the T2DM group (15.90%) compared to the control group (5.88%). However, this gap decreased substantially in the post-matching sample since the proportion of participants reporting poor general health at baseline was well balanced (15.90% in the T2DM group compared to 15.72% in the control group). Still some differences remain in terms of gender in the post matching sample which still sees a higher proportion of females with respect to males in the T2DM group (50.35%) compared to the control group (48.06 %). However, this

difference was much more pronounced in the pre-matching sample, which saw a lower proportion of females 48.06% in the T2DM group compared to the control group (56.55%). All of this indicates that the PSM approach worked well in making the T2DM group and control group more comparable in terms of characteristics at baseline.

**Table 4-4 Comparisons of baseline characteristics in the pre and post matching sample between the T2DM and control group.**

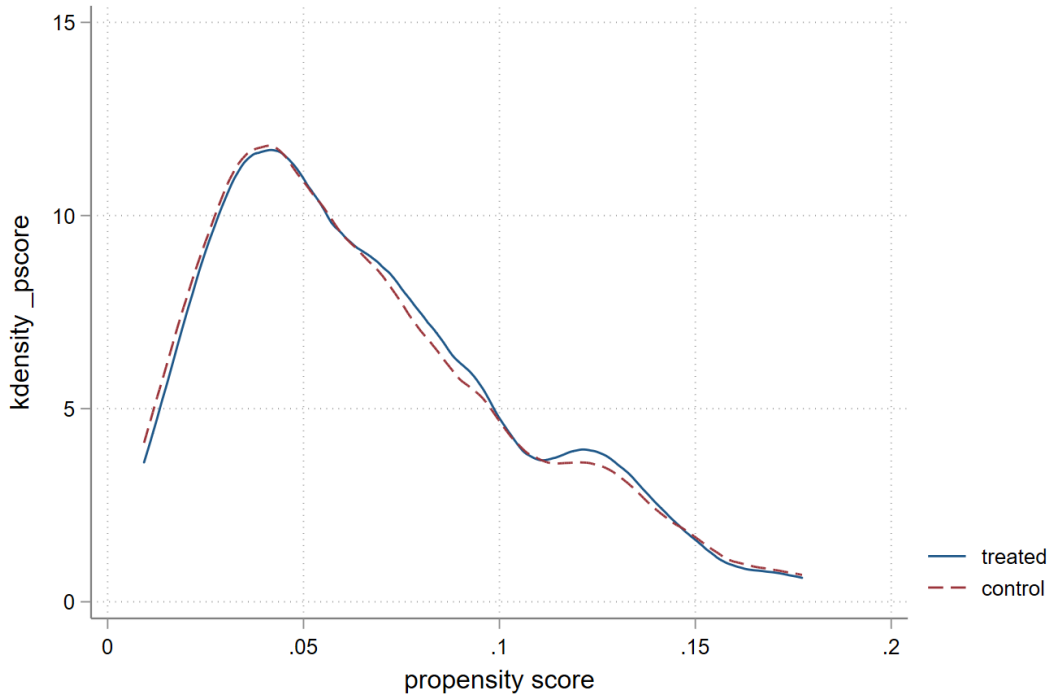
| | Pre-matching sample | | | | | Post matching sample | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Non T2DM Group (N=5,940) | T2DM group (N=283) | Overall (N=6,233) | P-value (T2DM group vs non T2DM Group) | | Non T2DM Group (N=928) | T2DM group (N=283) | Overall (N=1,211) | P-value (T2DM group vs non T2DM Group) |
| Age t0 | | | | | | | | | |
| Mean (SD) | 66.01(9.54) | 67.48(9.49) | 66.089(9.54) | 0.005 | | 67.35(9.15) | 67.48(9.49) | 67.42(9.32) | 0.869 |
| | | | | | | | | | |
| Median [Min, Max] | 64[50,99] | 67[50,91] | 65[50,99] | | | 67[50,99] | 67[50,91] | 67[50,99] | |
| | | | | | | | | | |
| Gender t0 | | | | | | | | | |
| Female | 3,359 (56.55%) | 136 (48.06%) | 3,495 (56.16%) | 0.005 | | 467 (50.35%) | 136 (48.06%) | 596 (49.20%) | 0.586 |
| Male | 2,581 (43.45%) | 147(51.94%) | 2,728 (43.82%) | | | 461(49.65%) | 147(51.94%) | 615(50.80%) | |
| Non-Pension Wealth t0 | | | | <0.001 | | | | | 0.976 |
| 1 (lowest) | 946 (15.93%) | 82 (28.98%) | 1,028 (16.52%) | | | 281 (30.30%) | 82 (28.98%) | 359 (29.64%) | |
| 2 | 1,141 (19.21%) | 66 (23.32%) | 1,207 (19.40%) | | | 213 (22.97%) | 66 (23.32%) | 280 (23.14%) | |
| 3 | 1,167 (19.65%) | 62 (21.91%) | 1,229 (19.75%) | | | 175 (18.90%) | 62 (21.91%) | 247 (20.41%) | |
| 4 | 1,323 (22.27%) | 38 (13.43%) | 1,361 (21.87%) | | | 138 (14.84%) | 38 (13.43%) | 171 (14.34%) | |
| 5(highest) | 1,363 (22.95%) | 35 (12.37%) | 1,398 (22.47%) | | | 121 (12.99%) | 35 (12.37%) | 154 (12.68%) | |
| General Health t0 | | | | <0.001 | | | | | 0.784 |
| Excellent | 927 (15.61%) | 20 (7.07%) | 947 (15.22%) | | | 56 (6.01%) | 20 (7.07%) | 79 (6.54%) | |
| Very Good | 1,926 (32.42%) | 43 (15.19%) | 1,969 (31.64%) | | | 145 (15.64%) | 43 (15.19%) | 187 (15.42%) | |
| Good | 1,798 (30.27%) | 94 (33.22%) | 1,892 (30.40%) | | | 304 (32.77%) | 94 (33.22%) | 400 (32.99%) | |
| Fair | 940 (15.82%) | 81 (28.62%) | 1,021 (16.41%) | | | 277 (29.86%) | 81 (28.62%) | 354 (29.42%) | |
| Poor | 349 (5.88%) | 45 (15.90%) | 394 (6.33%) | | | 146 (15.72%) | 45 (15.90%) | 191 (15.81%) | |

**Figure 4.2**




Figures 4.2 and 4.3 respectively show that the PSM approach has worked in balancing propensity scores between the T2DM group and control group.

**Figure 4.3**



### 4.4.4 Smoking

#### 4.4.4.1 Generalized Estimating Equations analysis.

Results from the population averaged panel data GEE model with smoking as the dependent variable are presented in table 4.5. There was a significant effect of time independent of group which saw the overall proportions of smokers to decrease over time both at T1 (β coefficient = -0.149; 95% CIs [-0.192 – 0.105], p-value <0.001) and T2 (β coefficient = -0.364; 95% CIs [-0.414 – 0.314], p-value <0.001). The coefficient for the variable group did not reach statistical significance suggesting that there is no difference in smoking between the T2DM and control group independent of time. Whereas the time by group interaction showed that the diagnosis of T2DM led to a larger change in smoking at T1 in the T2DM group compared to the control group (β coefficient = -0.279; 95% CIs [-0.449 – 0.0586]; p-value <0.05). However, this effect was only temporary (2-4 years after diagnosis) as suggested by the coefficient of T2 which did not reach statistical significance.

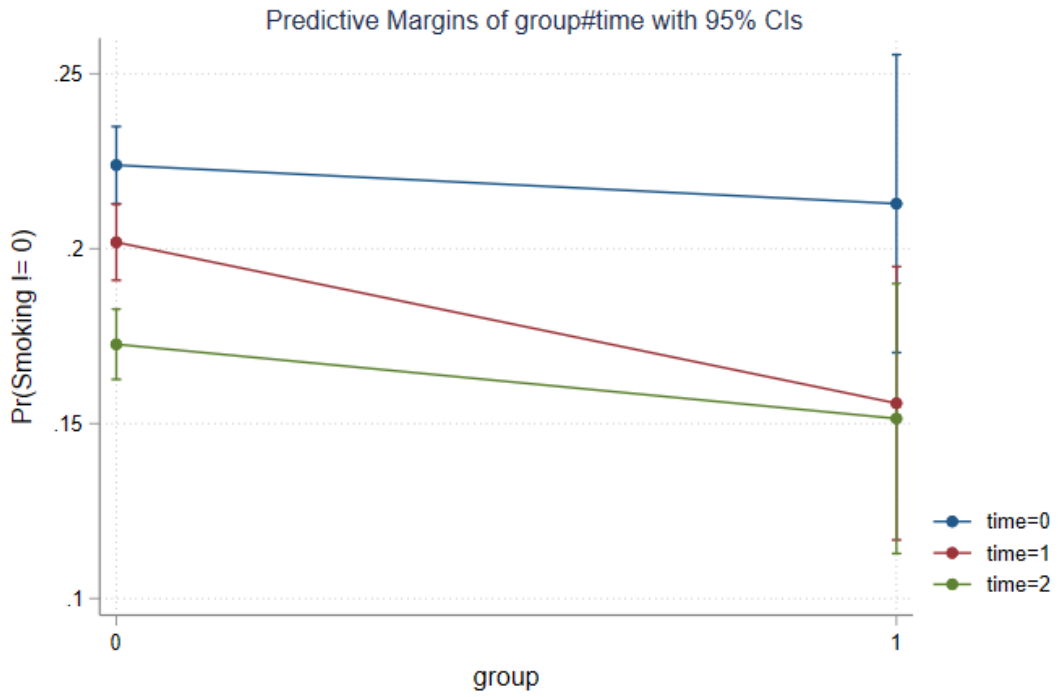
In terms of the effect of the covariates, individuals are less likely to smoke as their age increases ( β coefficient = -0.0625; 95% CIs [-0.070 – 0.054]; p-value <0.001), males are less likely to smoke compared to females (β coefficient = -0.214; 95% CIs [-0.350 – 0.0780]; p-value <0.05) and people from the highest wealth quintile are also less likely to smoke as shown by the coefficient for non-pension wealth which is monotonically decreasing. This effect is perfectly in line with the theoretical prediction from the Grossman model as hypothesised in section 4.1.3.

**Table 4-5 Coefficients and their respective 95% confidence intervals (CIs) from the full regression output with smoking as the dependent variable. p<0.001***, p<0.01**, p<0.05**

| Behaviour | Smoking | Cluster Robust Std. Err. | 95%CIs |
|---|---|---|---|
| Covariates | Coef. | | |
| Age (continuous – years) | -0.0625*** | 0.0041 | [-0.0706, -0.054] |
| Gender (Female ref.) | | | |
| Male | -0.214** | 0.0694 | [-0.350, -0.0780] |
| Non pension wealth (1 lowest) | | | |
| 2 | -0.756*** | 0.0964 | [-0.945, -0.568] |
| 3 | -1.048*** | 0.1018 | [-1.248, -0.849] |
| 4 | -1.598*** | 0.1118 | [-1.817, -1.379] |
| 5 (Highest) | -1.871*** | 0.1156 | [-2.098,-1.645] |
| Group (control ref.) | | | |
| T2DM | -0.0731 | 0.1511 | [-0.369,0.223] |
| Time (t0 ref) | | | |
| T1 | -0.149*** | 0.0222 | [-0.192, -0.105] |
| T2 | -0.364*** | 0.0254 | [-0.414, -0.314] |
| Time#group interaction | | | |
| T2DM#T1 | -0.279* | 0.1123 | [-0.499, -0.0586] |
| T2DM#T2 | -0.101 | 0.1269 | [-0.349,0.148] |
| _cons | 3.876*** | 0.2760 | [3.335,4.417] |
| N obs. | 21483 | | |
| Number of groups | 4867 | | |
| Observations per group | | | |
| Min | 3 | | |
| Avg | 4.4 | | |
| Max | 5 | | |
| QIC | 23937.414 | | |

A graphical representation of the predictive margins of the effect of the group by time interaction for smoking behaviour at three time points between the T2DM group and the control group is reported in Figure 4.3.

**Figure 4-3 Smoking behaviours at three times point in the T2DM (group1) and control (group 0) groups, respectively. All the proportions are adjusted for age, gender and non-pension wealth.**




### 4.4.4.2 Random Intercept Logit Model

Full regression results from the RE model are reported in table 4.6 and confirm the previous results from the GEE analysis. The group by time interaction suggests an incremental reduction in smoking in the T2DM group compared to the control group at T1 (β coefficient = -1.235; 95% CIs [-2.214; -0.0256]; p-value <0.001). Again, this effect disappeared at T2. However, as theorised in the section about methods 4.3.1.2 the beta coefficient is of greater magnitude as compared to the one from the GEE estimation (-1.235 vs 0.279; p-value <0.05 in both cases). There was a time effect since the proportion of individuals who

reported smoking decreased over time independent of the group. The time-invariant group variable was not significant as was the case for the GEE model.

The effect of the covariates also resembles results from the GEE models since older participants at baseline are less likely to smoke. Males are less likely to smoke compared to females, as they are people from the highest wealth quintiles compared to individuals in the lowest wealth quintiles.

The last part of table 4.6 provides estimates for the standard deviation of the random intercept sigma_u in addition to the estimated residual intra-class correlation rho. The former represents the between-subject standard deviation, whereas the latter denotes the within-cluster correlation. An estimate for the intra-class correlation of 0.95, as is the case for the model with smoking as the primary outcome, suggests a high degree of between-subjects heterogeneity or equivalently a hi-degree of within-subject correlation, among this behaviour. Considering this high value of rho not accounting for the dependence between different occasions within the same subject, e.g., a naïve approach would have represented a less than optimal method. This is because the pooled regression, e.g., the naive approach, is based on the assumption of zero intraclass correlation (uncorrelated residuals). The random effect approach, on the contrary, does one better than pooled regression and accounts for the dependence between responses within the same subject (cluster) via an individual-level random intercept ζj. Fitting an ordinary regression model with cluster robust standard errors would not have provided any information about the within and between cluster variances.

**Table 4-6 Maximum likelihood estimates with smoking behaviour as the dependent variable, and 95% confidence intervals. *p<0.05*p<0.1***p<0.01**

| Behaviour | Smoking | Std. Err. | 95%CIs |
|---|---|---|---|
| Age (year) | -0.211*** | 0.0141 | [-0.239,0.184] |
| Gender (female ref.) | | | |
| Male | -0.587** | 0.2127 | [-1.004,0.170] |
| Non pension wealth (1 lowest) | | | |
| 2 | -3.447*** | 0.3254 | [-4.085, -2.810] |
| 3 | -4.436*** | 0.3315 | [-5.086, -3.786] |
| 4 | -6.018*** | 0.3460 | [-6.697, -5.340] |
| 5(highest) | -6.549*** | 0.3537 | [-7.242, -5.855] |
| Group (control ref.) | | | |
| group | -0.0340 | 0.4546 | [-0.925,0.857] |
| T0 (ref) | | | |
| T1 | -0.761*** | 0.1148 | [-0.986,0.536] |
| T2 | -1.931*** | 0.1166 | [-2.160, -1.702] |
| Time#group interaction | | | |
| T2DM#T1 | -1.235* | 0.4994 | [-2.214, -0.256] |
| T2DM#T2 | -0.254 | 0.4880 | [-1.211,0.702] |
| _cons | 10.69*** | 0.9937 | [8.738,12.63] |
| | | | |
| lnsig2u | 4.351*** | | [4.266,4.436] |
| N | 21483 | | |
| Number of groups | 4,867 | | |
| Obs. per group | | | |
| Min | 3 | | |
| Avg | 4.4 | | |
| Max | 5 | | |
| *Sigma u* | 8.80 | 0.190 | [8.441, 9.187] |
| *Rho* | 0.95 | 0.0016 | [0.995,0.962] |
| *AIC* | 9649.952 | | |
| *BIC* | 9753.627 | | |

### 4.4.4.3 Propensity Score Matching

The full regression results from the random effect model on the matched sample (PSM model) table 4.7 do not match the previous results since the coefficient for T1 became non-significant suggesting that once the T2DM and control group are

balanced in terms of pre-treatment characteristics the incremental effect of the T2DM diagnosis of smoking behaviour disappears. There was still a significant time effect, and the impact of the other covariates was comparable to both the GEE and RE models.

**Table 4-7 Full regression results for the random effect model on the matched sample 95% Cis. *p<0.05**p<0.01***p<0.001.**

| Behaviour | Smoking | 95% CIs |
|---|---|---|
| | | |
| Age (year) | -0.167*** | [-0.244, -0.0888] |
| Gender (female ref.) | | |
| Male | -0.185 | [-1.283,0.914] |
| Non pension wealth (1 lowest ref.) | | |
| 2 | -2.942*** | [-4.623, -1.262] |
| 3 | -3.199*** | [-4.860, -1.538] |
| 4 | -4.905*** | [-7.079, -2.730] |
| 5 (highest) | -5.448*** | [-7.670, -3.226] |
| Group(control ref.) | | |
| T2DM | -0.461 | [-1.747,0.824] |
| T0 (ref) | | |
| T1 | -0.638* | [-1.196, -0.0790] |
| T2 | -1.098*** | [-1.674, -0.521] |
| Group#time interaction | | |
| T2DM#T1 | -1.041 | [-2.316,0.234] |
| T2DM#T2 | -0.550 | [-1.728,0.627] |
| _cons | 3.447 | [-2.569,9.464] |
| lnsig2u | 4.650*** | [4.450,4.850] |
| *N* | 5202 | |
| *Number of groups* | 1,211 | |
| *Obs. per group* | | |
| *Min* | 3 | |
| *Avg* | 4.3 | |
| *Max* | 5 | |
| *AIC* | 1954.277 | |
| *BIC* | 2065.742 | |

## 4.4.5 Alcohol

### 4.4.5.1 Generalized Estimating Equation Model

Table 4.8 shows the full GEE regression results for alcohol. There was a group effect since participants from the T2DM group were all else being equal less likely to drink (β coefficient = -0.488; 95% CIs [-0,833, -0.125]; p-value <0.05). The time effect was only significant at T2 (p-value <0.05) and the main effect of the group by time interaction was not significant suggesting no incremental impact of the T2DM diagnosis on the probability of drinking on a daily basis.

Regarding the effect of the other covariates, greater age at baseline was associated with an increased probability for the participants to drink with a frequency of five or more days a week (p-value <0.001). Males, with respect to females, were more likely to drink regularly (β coefficient = 0.353; 95% CIs [0,241, 0.465]; p-value <0.001), and participants from the highest wealth quintile were more likely to drink compared to the reference category of participants from the lowest quintile ( β coefficient = 0.682; 95% CIs [0,448, 0.971]; p-value <0.001) which is not consistent with the Grossman model prediction. However, it must be said that the variable for alcohol is looking at the frequency of alcohol consumption and not at the quantity of alcohol consumed.

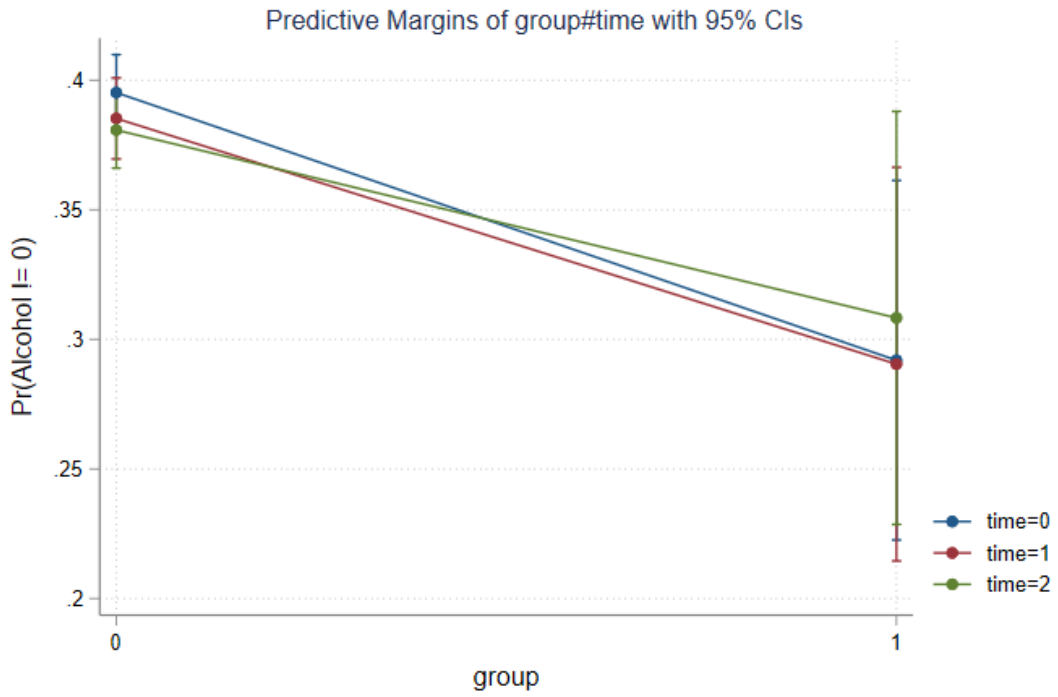
**Table 4-8 Coefficients and their respective 95% confidence intervals (CIs) from the full regression output with alcohol as the dependent variable. p<0.001***, p<0.01**, p<0.05***

| Behaviour | Alcohol | Cluster Robust Std. Err. | 95%CIs |
|---|---|---|---|
| Age | 0.0222*** | 0.00351 | [0.0155,0.0291] |
| | | | |
| Gender (Female ref. | | | |
| Male | 0.353*** | 0.0570 | [0.241,0.465] |
| Non pension wealth (1 lowest ref.) | | | |
| 2 | -0.152 | 0.1322 | [-0.412,0.107] |
| 3 | -0.0974 | 0.12825 | [-0.349,0.154] |
| 4 | 0.343** | 0.1222 | [0.103,0.582] |
| 5 | 0.682*** | 0.1197 | [0.448,0.917] |

| | | | |
|---|---|---|---|
| Group (control ref.) | | | |
| T2DM | -0.478* | 0.180 | [-0.833, -0.125] |
| Time (T0 ref.) | | | |
| T1 | -0.0437 | 0.0290 | [-0.101,0.0132] |
| T2 | -0.0634* | 0.0296 | [-0.122,0.0522] |
| Group#time interaction | | | |
| T2DM#T1 | 0.036 | 0.149 | [-0.257,0.329] |
| T2DM#T2 | 0.144 | 0.194 | [-0.236,0.524] |
| _cons | -2.334*** | 0.2567 | [-2.837, -1.830] |
| *N* | 15,582 | | |
| Number of groups | 3,705 | | |
| Obs per group | | | |
| Min | 3 | | |
| Avg | 4.2 | | |
| Max | 5 | | |
| QIC | 26848.550 | | |

Figure 4.6 shows the proportion of people who reported drinking daily which highlights again the presence of a group effect since participants in the intervention group were consistently less likely to drink compared to the control group independent of time and after adjusting for the covariates age, gender and non-pension wealth at T0.

**Figure 4-4 Alcohol consumption at three times points in the T2DM (group 1) and control (group 0) groups, respectively. All the proportions are adjusted for age, gender and non-pension wealth.**




### 4.4.5.2 Random Intercept Logit Model

Results from the RE model align with the previous GEE analysis and confirmed no significant effect of the T2DM diagnosis upon the likelihood to consume alcohol among the new diabetic participants Table 4.9 as the time by group effect suggests. There was a time effect but only at T2 (p-value <0.05) and a significant group effect (p-value <0.01). Also, results for the impact of the covariates match the previous GEE model and suggest that all else being equal, older participants at baseline are more likely to drink (p-value <0.001) as are male participants compared to females (p-value <0.001) and people from the highest wealth quintiles compared to people from the lowest quintile (p-value <0.001).

**Table 4-9 Maximum likelihood estimates for alcohol consumption as the dependent variable, cluster-robust standard errors and 95% confidence intervals. *p<0.10**p<0.05***p<0.01.**

| Behaviour | alcohol | Std. Err. | 95%CIs |
|---|---|---|---|
| | | | |
| Age | 0.0539*** | .0078 | [0.0385,0.0693] |
| Gender | | | |
| Male | 0.832*** | .1278 | [0.582,1.083] |
| Non pension wealth (1 lowest ref) | | | |
| 2 | -0.295 | .2810 | [-0.846,0.255] |
| 3 | -0.191 | .2704 | [-0.721,0.339] |
| 4 | 0.865*** | .2613 | [0.353,1.377] |
| 5(highest) | 1.652*** | .2561 | [1.150,2.154] |
| Group (control) | | | |
| T2DM | -1.084** | .3920 | [-1.852,-0.315] |
| T0 | | | |
| T1 | -0.102 | .0687 | [-0.236,0.0331] |
| T2 | -0.147* | .0614 | [-0.267,-0.0263] |
| Group#time interaction | | | |
| T2DM#T1 | 0.0905 | .3904 | [-0.675,0.856] |
| T2DM#T2 | 0.336 | .3637 | [-0.377,1.049] |
| _cons | -5.638*** | .5695 | [-6.754,-4.522] |
| | | | |
| lnsig2u | 2.428*** | | [2.323,2.533] |
| N | 15,582 | | |
| Number of groups | 3,705 | | |
| Min | 3 | | |
| Avg. | 4.2 | | |
| Max | 5 | | |
| Sigma u | 3.367 | 0.890 | [3.195,3.548] |
| Rho | 0.075 | 0.0093 | [0.0756,0.0793] |
| AIC | 15059.26 | | |
| BIC | 15158.76 | | |

### 4.4.5.3 Propensity Score Matching Analysis

Table 4.10 shows the results from the PSM analysis. There was no impact of the T2DM diagnosis on the probability of stopping drinking regularly. Still a significant group effect was detected even after balancing the T2DM and control group (p-value <0.001). The effect of gender and non-pension wealth matched with the one from the previous GEE and RE analysis, however the effect of age turned

not statically significant, suggesting no effect of age on the probability of drinking daily.

**Table 4-10 Results from the RE analysis on the matched sample and their 95% Cis and p-values. *p<0.10**p<0.05***p<0.0.**

| Behavior | Alcohol | 95% CIs |
|---|---|---|
| | | |
| Age (year) | 0.0118 | [-0.0209,0.0444] |
| Gender (female ref.) | | |
| Male | 2.049*** | [1.432,2.666] |
| Non pension wealth (1 lowest ref.) | | |
| 2 | 1.263** | [0.392,2.135] |
| 3 | 1.242** | [0.337,2.146] |
| 4 | 2.820*** | [1.872,3.767] |
| 5 (highest) | 4.412*** | [3.396,5.429] |
| Group (control ref.) | | |
| T2DM | -1.282** | [-2.157, -0.407] |
| Time (T0 ref.) | | |
| T0 | -0.154 | [-0.515,0.207] |
| T1 | -0.103 | [-0.416,0.211] |
| Group#time interaction | | |
| T2DM#T1 | 0.201 | [-0.679,1.082] |
| T2DM#T2 | 0.0406 | [-0.767,0.848] |
| _cons | -8.386*** | [-10.79, -5.982] |
| lnsig2u | 3.245*** | [3.068,3.422] |
| *N* | 5202 | |
| *Number of groups* | 1,211 | |
| *Obs. per group* | | |
| *Min* | 3 | |
| *Avg* | 4.3 | |
| *Max* | 5 | |
| *AIC* | 2953.925 | |
| *BIC* | 3065.39 | |

### 4.4.6 Physical activity

#### 4.4.6.1 Generalized Estimating Equation Model

The estimated coefficients from the fitted GEE model with the binary indicator for physical activity as the dependent variable are negative for age which means that all else being equal the log odds of being physically active are lower if age at

baseline increases (p-value <0.001) Table 4.11. Males compared to females are more likely to invest in their health and be physically active (p-value <0.001) as are individuals who earns more (p-value <0.001). There was a group effect since people in the T2DM group were less likely to be physically active compared to the control group independent of time. There was also a time effect (independent of group) given the negative coefficients of both T1 and T2 which indicates a decrease in the proportion of participants who are physically active over time after adjusting for age, gender, and non-pension wealth at T0. Again, the interaction term time by group is not significant suggesting no incremental effect of the T2DM diagnosis on the log odds of being physically active.

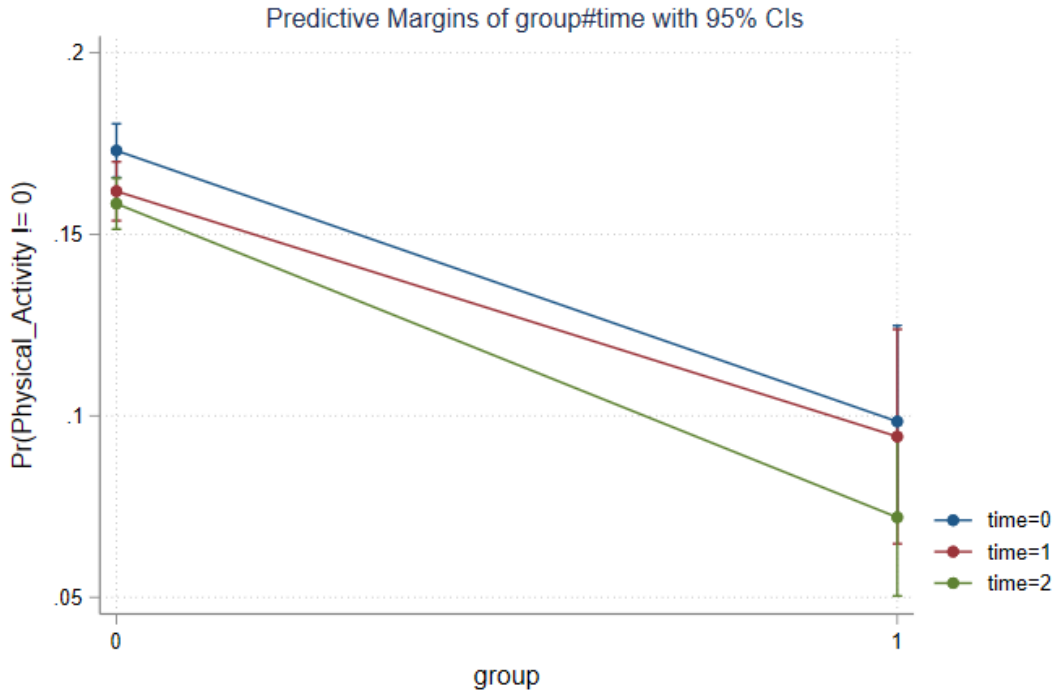
**Table 4-11 Maximum likelihood estimates for the binary GEE logistic regression model for physical activity.**

| Behaviour | Physical Activity | Cluster Robust Std. Err. | 95%CIs |
|---|---|---|---|
| | | | |
| Age (year) | -0.0547*** | 0.0025 | [-0.059,-0.049] |
| | | | |
| Gender (Female ref.) | | | |
| Male | 0.304*** | 0.0449 | [0.216,0.393] |
| Non pension wealth (1 lowest ref.) | | | |
| 2 | 0.426*** | 0.0945 | [0.240,0.611] |
| 3 | 0.788*** | 0.0904 | [0.609,0.964] |
| 4 | 0.985*** | 0.0887 | [0.811,1.159] |
| 5 (highest) | 1.363*** | 0.0855 | [1.196,1.531] |
| Group (control ref.) | | | |
| T2DM | -0.683*** | 0.1600 | [-0.997, -0.370] |
| Time | | | |
| T1 | -0.0853** | 0.0328 | [-0.150, -0.0209] |
| T2 | -0.112*** | 0.0310 | [-0.173, -0.0514] |
| T2DM#T1 | 0.357 | 0.2081 | [-0.372,0.443] |
| T2DM#T2 | -0.240 | 0.206 | [-0.644,0.164] |
| _cons | 0.954*** | 0.1801 | [0.601,1.307] |
| *N* | 34,879 | | |
| Number of groups | 7,863 | | |

| | | | |
|---|---|---|---|
| Observations per group | | | |
| Min | 3 | | |
| Avg | 4.4 | | |
| Max | 5 | | |
| QIC | 29008.178 | | |

As reported in figure 4.8, the proportion of participants who reported taking part in vigorous exercise at least once a week was lower in the T2DM group (group 1) compared to the control group (group 0) regardless of time which confirms the group effect mentioned in the previous paragraph.

**Figure 4-5 Physical activity at three times points in the T2DM (group 1) and control (group 0) groups, respectively. All the proportions are adjusted for age, gender and non-pension wealth.**



### 4.4.6.2 Random Intercept Logit Model

The signs of estimated coefficient from the RE model table 4.12 are concordant with the values described in the GEE analysis overall. There was no impact of the T2DM diagnosis on the log odds of being physically active.

**Table 4-12 Maximum likelihood estimates for the binary RE logistic regression model for physical activity as dependent variable *p<0.10**p<0.05***p<0.01.**

| Behaviour | Physical Activity | Std. Err. | 95%CIs |
|---|---|---|---|
| | | | |
| Age | -0.0853*** | 0.0041 | [0.0934,0.077] |
| Gender (female ref.) | | | |
| Male | 0.513*** | 0.0675 | [0.381,0.646] |
| Non pension wealth (1 lowest ref.) | | | |
| 2 | 0.643*** | 0.1298 | [0.389,0.898] |
| 3 | 1.169*** | 0.1260 | [0.922,1.416] |
| 4 | 1.475*** | 0.1234 | [1.233,1.717] |
| 5 (highest) | 2.066*** | 0.1210 | [1.828,2.303] |
| Group (control ref.) | | | |
| T2DM | -0.979*** | 0.2162 | [-1.403, -0.555] |
| T0 | | | |
| T1 | -0.131** | 0.0504 | [-0.230, -0.032] |
| T2 | -0.172*** | 0.0432 | [-0.256, -0.086] |
| Group#time interaction | | | |
| T2DM#T1 | 0.0581 | 0.2743 | [-0.480,0.596] |
| T2DM#T2 | -0.306 | 0.2611 | [-0.818,0.206] |
| _cons | 1.437*** | 0.2784 | [0.892,1.983] |
| | | | |
| lnsig2u | 1.464*** | | [1.380,1.548] |
| *N* | 34879 | | |
| Number of groups | 7,863 | | |
| Obs. per group | | | |
| Min | 3 | | |
| Avg | 4.4 | | |
| Max | 5 | | |
| Sigma u | 2.079 | 0.0046 | [1.994,2.169] |
| Rho | 0.0568 | 0.0105 | [0.0547,0.0588] |
| AIC | 25164.6 | | |
| BIC | 25274.57 | | |

#### 4.4.6.3 Propensity Score Matching Model

Results from the RE model on the matched sample still show no effect of the T2DM diagnosis on the probability of being physically active. However, once the differences at baseline between the T2DM and control group are balanced the group effect was not observed anymore. Age has still a negative sign as in the previous models suggesting that as age at T0 increases individuals are less likely to invest their health and be physically active.

The effect of non-pension wealth was still detected but from the third quintiles onwards only.

**Table 4-13 Maximum likelihood estimates for the binary RE logistic regression model on the matched sample for physical activity as dependent variable *p<0.10**p<0.05***p<0.01.**

| Behaviour | Physical Activity | 95% Cis |
|---|---|---|
| Age | -0.0761*** | [-0.0999, -0.0523] |
| Gender (female ref.) | | |
| Male | 0.776*** | [0.363,1.190] |
| Non pension wealth (1 lowest ref.) | | |
| 2 | 0.548 | [-0.0883,1.185] |
| 3 | 1.486*** | [0.861,2.111] |
| 4 | 1.345*** | [0.686,2.004] |
| 5 | 2.311*** | [1.669,2.952] |
| Group | | |
| T2DM | -0.290 | [-0.894,0.314] |
| Time (T0 ref.) | | |
| T1 | 0.0657 | [-0.261,0.392] |
| T2 | -0.112 | [-0.400,0.176] |
| Group#time interaction | | |
| T2DM#T1 | -0.135 | [-0.871,0.601] |
| T2DM#T2 | -0.575 | [-1.277,0.126] |
| _cons | -0.0167 | [-1.636,1.602] |
| lnsig2u | 1.569*** | [1.315,1.824] |
| *N* | 5202 | |
| *Number of groups* | 1,211 | |
| *Number of obs per group* | | |
| *Min* | 3 | |
| *Avg* | 4.3 | |
| *Max* | 5 | |
| *AIC* | 2742.536 | |
| *BIC* | 2854.002 | |

### 4.4.7 Sedentary behaviour

#### 4.4.7.1 Generalized Estimating Equation Model

Results from the GEE model table 4.14 indicate a group effect such as people from the T2DM group were more likely to conduct a sedentary lifestyle (p-value <0.001). The coefficients for both T1 and T2 are positive which indicates the presence of a time effect i.e., an increase in sedentary behaviour over time independent of the group. As it was the case for physical activity and alcohol, there was still no statistically significant effect of the time by group interaction terms on the log odds of conducting a sedentary lifestyle at 5 % level.

Among the covariates age displays a positive sign, which indicates that as the participants grow older, they will be more likely to conduct a sedentary lifestyle. Conversely, males with respect to females are less likely to engage in sedentary behaviour as are people in the highest non pension wealth quintiles compared to people in the lowest quintile.

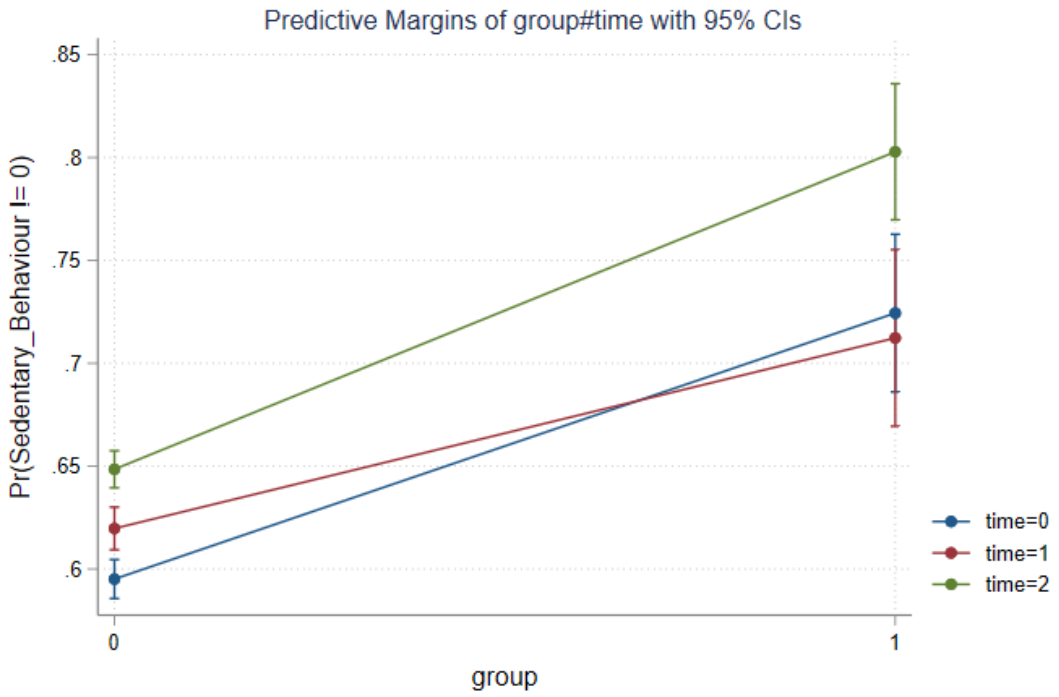
**Table 4-14 Estimates for the binary GEE logistic regression model for sedentary behaviour as dependent variable *p<0.10**p<0.05***p<0.01.**

| Behaviour | Sedentary behaviour | Robust Std. Err. | 95% CIs |
|---|---|---|---|
| | | | |
| Age | 0.0530*** | 0.0020 | [0.0490,0.0570] |
| | | | |
| Gender (Female ref. | | | |
| Male | -0.460*** | 0.0365 | [-0.532, -0.388] |
| Non pension wealth (1 lowest ref.) | | | |
| 2 | -0.476*** | 0.0698 | [-0.613, -0.339] |
| 3 | -0.913*** | 0.067 | [-1.046, -0.781] |
| 4 | -1.134*** | 0.0670 | [-1.266, -1.003] |
| 5 | -1.512*** | 0.0657 | [-1.648, -1.391] |
| Group (control ref.) | | | |
| T2DM | 0.649*** | 0.1102 | [0.433,0.864] |

| | | | |
|---|---|---|---|
| Time (T0 ref.) | | | |
| T1 | 0.116*** | 0.0245 | [0.0680,0.164] |
| T2 | 0.255*** | 0.0236 | [0.209,0.302] |
| Group#interaction | | | |
| T2DM#T1 | -0.182 | 0.1289 | [-0.435,0.070] |
| T2DM#T2 | 0.222 | 0.1312 | [-0.0345,0.479] |
| _cons | -1.956*** | 0.143 | [-2.236,-1.68] |
| *N* | 34,879 | | |
| Number of groups | 7,863 | | |
| Observations per group | | | |
| Min | 3 | | |
| Avg | 4.4 | | |
| Max | 5 | | |
| QIC | 23937.414 | | |

The time and group effects are confirmed graphically in figure 4.9, which shows both a greater proportion of participants who conduct a sedentary lifestyle in the T2DM group compared to the control group and an increase over time in the proportion of people engaged in sedentary behaviour regardless of group.

**Figure 4-6 Sedentary behaviour at three times point in the T2DM (group 1) and control (group 0) groups, respectively. All the proportions are adjusted for age, gender, and non-pension wealth.**




### 4.4.7.2 Random Intercept Logit Model

Results from the RE model table 4.15 are concordant with the previous GEE model and show no impact of the T2DM diagnosis on sedentary behaviour. Both the group effect and the time effect are still significant with p-values <0.001 in both cases. The effect of the other covariates also remained unchanged.

The rho value equivalent to 0.585 suggests a lower degree of within-subject correlation among this behaviour compared to smoking.

**Table 4-15 Maximum likelihood estimates from the RE model for sedentary behaviour as the dependent variable, cluster-robust standard errors and 95% confidence intervals. *p<0.10**p<0.05***p<0.01.**

| Behaviour | Sedentary behaviour | Cluster.Rob.Std. Err. | 95% CIs |
|---|---|---|---|
| | | | |
| Age (year) | 0.0905*** | 0.0041 | [0.0836,0.0975] |

| | | | |
|---|---|---|---|
| Gender (female ref.) | | | |
| Male | -0.780*** | 0.0675 | [-0.901,-0.660] |
| Non pension wealth (1 lowest ref.) | . | | |
| 2 | -0.765*** | 0.1298 | [-0.978,-0.551] |
| 3 | -1.487*** | 0.1260 | [-1.697, -1.277] |
| 4 | -1.864*** | 0.1234 | [-2.072, -1.656] |
| 5 | -2.521*** | 0.1210 | [-2.728, -2.314] |
| Group (control ref.) | | | |
| T2DM | 1.049*** | 0.167 | [0.717,1.382] |
| Time (T0 ref.) | | | |
| T1 | 0.196*** | 0.041 | [0.114,0.277] |
| T2 | 0.429*** | 0.036 | [0.358,0.500] |
| Group#time interaction | | | |
| T2DM#T1 | -0.298 | 0.192 | [-0.674,0.0786] |
| T2DM#T2 | 0.298 | 0.185 | [-0.0644,0.661] |
| _cons | -3.396*** | 0.243 | [-3.872, -2.920] |
| lnsig2u | 1.534*** | | [1.464,1.603] |
| *N* | 34879 | | |
| Number of groups | 7,863 | | |
| Obs per group | | | |
| Min | 3 | | |
| Avg | 4.4 | | |
| Max | 5 | | |
| Sigma u | 2.152 | 0.038 | [2.079,2.229] |
| Rho | 0.585 | 0.008 | [0.568,0.602] |
| AIC | 35812.65 | | |
| BIC | 35922.63 | | |

#### 4.4.7.3 Propensity Score Matching analysis

The coefficient presented in table 4.16 resemble the ones from the previous models and show no impact of T2DM diagnosis on the log odds of conducting a sedentary lifestyle. The coefficient for group became not significant which suggests that once the covariates at baseline are balanced between the T2DM and control group, the group effect is not observed anymore. The time effect was only significant at T2 whereas the effect of the covariates remained unchanged with respect to the previous models.

**Table 4-16 Maximum likelihood estimates for the binary RE logistic regression model on the matched sample for sedentary behaviour as dependent variable *p<0.05*p<0.01**p<0.001*****

| Behaviour | Sedentary behaviour | 95% CIs |
|---|---|---|
| Age (year) | 0.0890*** | [0.0700,0.108] |
| Gender (female ref.) | | |
| Male | -0.982*** | [-1.314, -0.650] |
| Non pension wealth (1 lowest ref.) | | |
| 2 | -0.995*** | [-1.479, -0.511] |
| 3 | -1.707*** | [-2.205, -1.208] |
| 4 | -1.781*** | [-2.305, -1.257] |
| 5 | -2.433*** | [-2.966, -1.900] |
| Group (control ref.) | | |
| T2DM | 0.439 | [-0.0260,0.905] |
| Time | | |
| T1 | 0.220 | [-0.0278,0.468] |
| T2 | 0.566*** | [0.345,0.788] |
| Group#time interaction | | |
| T2DM#T1 | -0.454 | [-0.974,0.0653] |
| T2DM#T2 | 0.228 | [-0.261,0.717] |
| _cons | -2.672*** | [-3.972, -1.371] |
| lnsig2u | 1.556*** | [1.362,1.750] |
| *N* | 5202 | |
| *Number of groups* | 1,211 | |
| *Number of obs per group* | | |
| *Min* | 3 | |
| *Avg* | 4.3 | |
| *Max* | 5 | |
| *AIC* | 4561.716 | |
| *BIC* | 4673.182 | |

## 4.4.8 Fruit and vegetable consumption

### 4.4.8.1 Generalized Estimating Equation Model

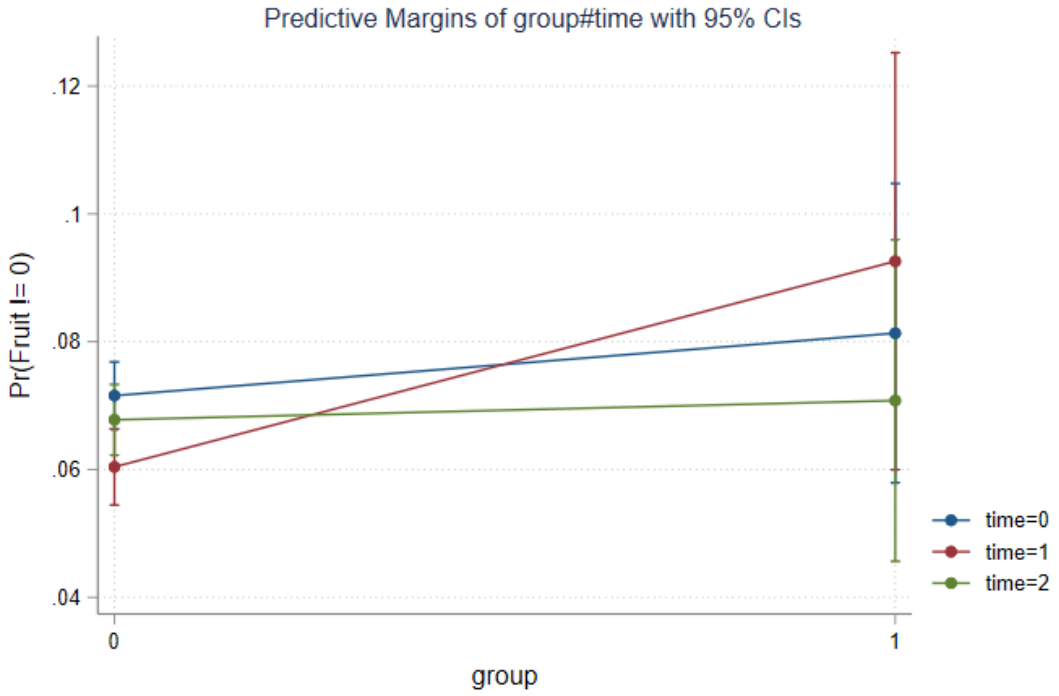
The coefficient for the time by group interaction was not significant suggesting no impact of the T2DM diagnosis on the log odds of eating at least five portions of fruit and vegetable for the participants recently diagnosed with T2DM compared to control. There was no group effect, and the time effect was detected only at T1 (p-value <0.01). As participants get older, they slightly increase the probability of investing in their health by eating their five a day, but no other effect was detected among covariates.

**Table 4-17 Maximum likelihood estimates for the binary GEE logistic regression models for fruit as the dependent variable *p<0.10**p<0.05***p<0.01.**

| Behaviour | Fruit | Robust Std. Err. | 95% CIs |
|---|---|---|---|
| Age (year) | -0.0107** | 0.0032 | [-0.0170, -0.004] |
| | | | |
| Gender (Female ref.) | | | |
| Male | -0.0211 | 0.0586 | [-0.136,0.093] |
| Non pension wealth (1 lowest ref.) | | | |
| 2 | -0.1789 | 0.1045 | [-0.383,0.0261] |
| 3 | -0.103 | 0.1020 | [-0.303,0.097] |
| 4 | -0.216* | 0.1013 | [-0.414,-0.0171] |
| 5 | -0.044 | 0.0978 | [-0.236,0.148] |
| Group (control ref) | | | |
| T2DM | 0.139 | 0.1652 | [-0.185,0.462] |
| Time | | | |
| T1 | -0.181** | 0.0652 | [-0.309,-0.0535] |
| T2 | -0.0584 | 0.0583 | [-0.173,0.0562] |
| Group#time interaction | | | |
| T2DM#T1 | 0.323 | 0.2391 | [-0.145,0.792] |
| T2DM#T2 | -0.0092 | 0.2351 | [-0.552,0.366] |
| _cons | -1.747*** | 0.2278 | [-2.196,-1.301] |
| *N* | 27679 | | |
| Number of groups | 6,443 | | |
| Observation per group | | | |
| Min | 3 | | |
| Avg | 4.3 | | |
| Max | 5 | | |
| QIC | 42194.589 | | |

The proportion of participants who reported consuming at least five portions of fruit or vegetables for each of the group over time are presented in figure 4.10.

**Figure 4-7 Fruit and vegetable consumption at three times point in the T2DM (group 1) and control (group 0) groups, respectively. All the proportions are adjusted for age, gender and non-pension wealth.**




### 4.4.8.2 Random Intercept Logit Model

As table 4.18 indicates results for the RE model are concordant with the previous GEE model and no significant changes were observed for the frequency of fruit and vegetable intake among the participants newly diagnosed with T2DM compared to their counterparts who never had a T2DM diagnosis throughout the period covered by this study. The group effect was not significant, and the time effect was only detected at T1 (p-value <0.01). The effect of age is also consistent with the previous GEE model (p-value <0.01).

**Table 4-18 Maximum likelihood estimates for the RE model with fruit and vegetable consumption as the dependent variable, cluster-robust standard errors and 95% confidence intervals. *p<0.10**p<0.05***p<0.01.**

| Behaviour | Fruit | Std. Err. | 95% CIs |
|---|---|---|---|
| Age (year) | -0.0129** | 0.0039 | [-0.020, -0.005] |
| Gender (female ref.) | | | |
| Male | -0.0130 | 0.0682 | [-0.147,0.121] |
| Non pension wealth (1 lowest ref.) | | | |
| 2 | -0.196 | 0.1206 | [0.432,0.0404] |
| 3 | -0.114 | 0.1172 | [-0.344,0.116] |
| 4 | -0.245* | 0.1164 | [-0.473,0.016] |
| 5 (highest) | -0.0417 | 0.1125 | [-0.262,0.179] |
| Group (control ref.) | | | |
| T2DM | 0.152 | 0.2067 | [-0.254,0.557] |
| Time (T0 ref.) | | | |
| T1 | -0.213** | 0.0717 | [-0.353,0.072] |
| T2 | -0.0713 | 0.0605 | [0.190,0.0474] |
| Group#time interaction | | | |
| T2DM#T1 | 0.385 | 0.2892 | [-0.181,0.952] |
| T2DM#T2 | -0.103 | 0.2743 | [-0.640,0.435] |
| _cons | -2.357*** | 0.2833 | [-2.912,1.802] |
| | | | |
| lnsig2u | 0.703*** | | [0.561,0.845] |
| *N* | 27679 | | |
| Number of groups | 6,443 | | |
| Obs. per group | | | |
| Min | 3 | | |
| Avg | 4.3 | | |
| Mx | 5 | | |
| Sigma u | 1.421 | 0.0515 | [1.324,1,526] |
| Rho | 0.380 | 0.171 | [0.0348,0.414] |
| AIC | 13213.36 | | |
| BIC | 13320.32 | | |

### 4.4.8.3 Propensity Score Matching Analysis

The results from the PSM analysis showed no difference among the proportion of the participants who self-reported to eat at least five portions of fruit and vegetable daily between the T2DM group and control group table 4.19. There was no time effect after the T2DM, and control groups were balanced in their

characteristics at baseline. Estimates for age are in line with the results from the previous models.

**Table 4-19 Maximum likelihood estimates for the RE model with fruit and vegetable consumption as the dependent variable on the matched sample and 95% confidence intervals. *p<0.10**p<0.05***p<0.01.**

| Behaviour | Fruit | 95% CIs |
|---|---|---|
| Age (year) | -0.0233* | [-0.0431,-0.00338] |
| Gender (female ref.) | | |
| Male | -0.0860 | [-0.449,0.277] |
| Non pension wealth | | |
| 2 | 0.492 | [-0.00848,0.992] |
| 3 | 0.126 | [-0.419,0.670] |
| 4 | -0.00728 | [-0.600,0.586] |
| 5 (highest) | 0.379 | [-0.192,0.950] |
| Group (control ref.) | | |
| T2DM | 0.429 | [-0.117,0.975] |
| Time (T0 ref.) | | |
| T1 | 0.0394 | [-0.337,0.416] |
| T2 | -0.0854 | [-0.423,0.252] |
| Group#time interaction | 0 | [0,0] |
| T2DM#T1 | 0.238 | [-0.465,0.942] |
| T2DM#T2 | -0.0915 | [-0.751,0.567] |
| _cons | -2.495*** | [-3.922,-1.068] |
| lnsig2u | 1.142*** | [0.837,1.447] |
| *N* | 5202 | |
| *Number of groups* | 1,211 | |
| *Obs. per group* | | |
| *Min* | 3 | |
| *Avg* | 4.3 | |
| *Max* | 5 | |
| *AIC* | 2354.958 | |
| *BIC* | 2466.424 | |

### 4.4.9 Sensitivity analysis 1

Following the exact same approach as Hackett et al.,2018 a set of sensitivities analysis was also performed. In the first sensitivity analysis, education was included among the covariates table 4.20.

## Table 4-20 Results from the first sensitivity analysis

| Model | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Behaviour | smoking | 95 CIs | alcohol | 95 CIs | physical activity | 95 CIs | fruit | 95 CIs | Sedentary behaviour | 95 CIs |
| Age (year) | -0.0671*** | [0.075,0.0587] | 0.0253*** | [0.0183,0.0323] | -0.0507*** | [-0.055,-0.045] | -0.00970** | [-0.0161,0.003] | 0.0486*** | [0.0445,0.0527] |
| Gender (female ref.) | | | | | | | | | | |
| Male | -0.180** | [-0.317,-0.043] | 0.308*** | [0.196,0.421] | 0.259*** | [0.170,0.348] | -0.0300 | [-0.147,0.0866] | -0.409*** | [-0.482,-0.337] |
| Non pension wealth (1 lowest) | | | | | | | | | | |
| 2. | -0.718*** | [-0.908,-0.528] | -0.166 | [-0.426,0.0948] | 0.384*** | [0.197,0.570] | -0.190 | [-0.397,0.0171] | -0.432*** | [-0.569,-0.295] |
| 3 | -0.965*** | [-1.167,-0.764] | -0.142 | [-0.395,0.112] | 0.709*** | [0.528,0.890] | -0.129 | [-0.333,0.0752] | -0.826*** | [-0.960,-0.692] |
| 4 | -1.458*** | [-1.683,-1.233] | 0.257* | [0.0129,0.501] | 0.863*** | [0.684,1.043] | -0.239* | [-0.443,-0.0346] | -0.993*** | [-1.127,-0.858] |
| 5 (highest) | -1.683*** | [-1.918,-1.447] | 0.550*** | [0.309,0.791] | 1.190*** | [1.013,1.368] | -0.0794 | [-0.281,0.122] | -1.317*** | [-1.451,-1.183] |
| Education (no qual ref.) | | | | | | | | | | |
| High school | -0.266*** | [-0.414,-0.118] | 0.128 | [-0.0360,0.292] | 0.226*** | [0.101,0.352] | 0.0184 | [-0.136,0.173] | -0.290*** | [-0.383,-0.197] |
| College degree | -0.621*** | [-0.849,-0.392] | 0.470*** | [0.282,0.658] | 0.536*** | [0.386,0.685] | 0.105 | [-0.0863,0.296] | -0.645*** | [-0.762,-0.527] |
| Group (control ref.) | | | | | | | | | | |
| T2DM | -0.105 | [-0.407,0.197] | -0.473** | [-0.820,-0.125] | -0.657*** | [-0.974,-0.341] | 0.128 | [-0.200,0.456] | 0.629*** | [0.412,0.846] |
| Time (T0 ref.) | | | | | | | | | | |
| T1 | -0.147*** | [-0.191,-0.103] | -0.0481 | [-0.106,0.00943] | -0.0911** | [-0.156,-0.026] | -0.175** | [-0.304,-0.0469] | 0.121*** | [0.0719,0.170] |
| T2 | -0.363*** | [-0.414,-0.313] | -0.0679* | [-0.127,-0.00910] | -0.118*** | [-0.180,-0.056] | -0.0519 | [-0.167,0.0630] | 0.261*** | [0.214,0.309] |
| Group#time interaction | | | | | | | | | | |
| T2DM#T1 | -0.251* | [-0.468,-0.034] | 0.0421 | [-0.253,0.338] | 0.0420 | [-0.368,0.451] | 0.338 | [-0.132,0.809] | -0.195 | [-0.449,0.0594] |
| T2DM#T2 | -0.0704 | [-0.316,0.175] | 0.148 | [-0.233,0.529] | -0.237 | [-0.643,0.169] | -0.0789 | [-0.541,0.384] | 0.214 | [-0.0445,0.472] |
| _cons | 4.309*** | [3.730,4.888] | -2.618*** | [-3.155,-2.082] | 0.580** | [0.208,0.952] | -1.827*** | [-2.304,-1.351] | -1.507*** | [-1.802,-1.211] |
| *N* | 21402 | | 15524 | | 34730 | | 27573 | | 34730 | |

The results did not differ from the previous estimation for each behaviour investigated during this analysis. The coefficients for education are negative for smoking, positive for physical activity and again negative for sedentary behaviour, suggesting that the more educated people, all else being equal, are more likely to invest in their health, e.g., less likely to smoke and be sedentary and more likely to be physically active.

In the second sensitivity analysis of this section, BMI was added as an additional variable table 4.21. The negative effect of the time by group interaction at T1 became not significant for smoking (model 1). Apart from this, the addition of BMI did not change the results compared to the previous GEE models.

In the last sensitivity analysis, participants in the control group who reported sedentary behaviour were excluded from the sample table 4.22. This made to compare the T2DM group to a healthy control group as it was done by Hackett et al., 2019. The group by time interaction became statistically significant again at 5% level for smoking (model 1). With the exclusion of this exception results did not change substantially from prior estimations.

## Table 4-21 Results from the second sensitivity analysis

| Model | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Behaviour | smoking | 95% CIs | alcohol | 95% CIs | Physical activity | 95% CIs | fruit | 95% CIs | Sedentary behaviour | 95% CIs |
| Age (year) | -0.068*** | [-0.078,0.059] | 0.0262*** | [0.0187,0.0337] | -0.0511*** | [-0.057,-0.046] | -0.0092** | [-0.0162,0.0023] | 0.0477*** | [0.0432,0.0523] |
| Gender (Female ref.) | | | | | | | | | | |
| Male | -0.184* | [-0.337,0.0311] | 0.300*** | [0.181,0.420] | 0.270*** | [0.176,0.364] | -0.0264 | [-0.150,0.0972] | -0.414*** | [-0.491,-0.337] |
| Non pension wealth (1 lowest ref.) | | | | | | | | | | |
| 2 | -0.732*** | [-0.945,-0.519] | -0.139 | [-0.419,0.141] | 0.368*** | [0.168,0.567] | -0.215 | [-0.435,0.00559] | -0.341*** | [-0.489,-0.193] |
| 3 | -0.948*** | [-1.177,-0.719] | -0.109 | [-0.382,0.165] | 0.649*** | [0.454,0.844] | -0.141 | [-0.357,0.0759] | -0.724*** | [-0.869,-0.580] |
| 4 | -1.491*** | [-1.742,-1.239] | 0.270* | [0.00697,0.533] | 0.766*** | [0.572,0.959] | -0.257* | [-0.476,-0.0384] | -0.847*** | [-0.992,-0.702] |
| 5 (highest) | -1.832*** | [-2.099,-1.565] | 0.546*** | [0.286,0.806] | 1.079*** | [0.889,1.270] | -0.145 | [-0.359,0.0692] | -1.132*** | [-1.277,-0.987] |
| Education (no qual.ref.) | | | | | | | | | | |
| High school | -0.308*** | [-0.473,-0.142] | 0.126 | [-0.0481,0.299] | 0.171* | [0.0359,0.305] | 0.00418 | [-0.159,0.167] | -0.271*** | [-0.371,-0.170] |
| College degree | -0.724*** | [-0.987,-0.462] | 0.478*** | [0.279,0.677] | 0.451*** | [0.291,0.612] | 0.138 | [-0.0630,0.340] | -0.610*** | [-0.737,-0.483] |
| | | | | | | | | | | |
| BMI (kg/m2) | -0.090*** | [-0.108,-0.073] | -0.0210** | [-0.0351,-0.007] | -0.0500*** | [-0.0602-0.039] | 0.0105 | [-0.0008,0.0218] | 0.0455*** | [0.0376,0.0535] |
| | | | | | | | | | | |
| Group (control ref.) | | | | | | | | | | |
| T2DM | 0.250 | [-0.0903,0.591] | -0.312 | [-0.670,0.0463] | -0.597** | [-0.953,-0.241] | 0.0475 | [-0.322,0.417] | 0.558*** | [0.308,0.809] |
| Time (T0 ref.) | . | | | | | | | | | |
| T1 | -0.178*** | [-0.229,-0.127] | -0.0269 | [-0.0871,0.0333] | -0.0841* | [-0.153,-0.015] | -0.203** | [-0.339,-0.0660] | 0.125*** | [0.0719,0.178] |
| T2 | -0.398*** | [-0.456,-0.341] | -0.0588 | [-0.120,0.00254] | -0.117*** | [-0.183,-0.052] | -0.0782 | [-0.200,0.0432] | 0.263*** | [0.212,0.313] |
| Group#time | . | | | | . | | . | | | |
| T2DM#T1 | -0.132 | [-0.356,0.0911] | 0.0347 | [-0.286,0.355] | 0.160 | [-0.297,0.618] | 0.310 | [-0.220,0.839] | -0.212 | [-0.506,0.0819] |
| T2DM#T2 | 0.0713 | [-0.194,0.337] | 0.104 | [-0.307,0.514] | -0.0620 | [-0.502,0.378] | -0.146 | [-0.655,0.364] | 0.149 | [-0.143,0.440] |
| _cons | 6.920*** | [6.083,7.757] | -2.131*** | [-2.842,-1.420] | 2.150*** | [1.643,2.658] | -2.116*** | [-2.750,-1.482] | -2.912*** | [-3.330,-2.493] |
| *N* | 18124 | | 14067 | | 29538 | | 24539 | | 29538 | |

## Table 4-22 Results from the third sensitivity analysis

| Model | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Behaviour | smoking | 95% CIs | alcohol | 95% CIs | Physical activity | 95% CIs | fruit | 95% CIs | sedentary behaviour | 95% CIs |
| Age (year) | -0.064*** | [-0.075,0.053] | 0.0213*** | [0.0132,0.0293] | -0.0455*** | [-0.051,0.039] | -0.0081* | [0.016,0.0006] | 0.0444*** | [0.0398,0.0491] |
| Gender (female ref.) | | | . | | | | | | | |
| Male | -0.182* | [-0.353,-0.011] | 0.406*** | [0.277,0.534] | 0.214*** | [0.118,0.311] | -0.0558 | [-0.191,0.078] | -0.424*** | [-0.505,-0.342] |
| Non pension wealth (1 lowest ref.) | | | | | | | | | | |
| 2 | -0.657*** | [-0.911,-0.403] | -0.180 | [-0.515,0.155] | 0.297** | [0.0833,0.510] | -0.247 | [-0.507,0.012] | -0.264** | [-0.422,-0.106] |
| 3 | -0.914*** | [-1.176,-0.652] | -0.117 | [-0.443,0.209] | 0.546*** | [0.341,0.750] | -0.198 | [-0.452,0.056] | -0.622*** | [-0.774,-0.471] |
| 4 | -1.528*** | [-1.810,-1.247] | 0.330* | [0.0184,0.641] | 0.744*** | [0.543,0.944] | -0.247 | [-0.494,0.001] | -0.807*** | [-0.957,-0.656] |
| 5 (highest) | -1.778*** | [-2.061,-1.495] | 0.699*** | [0.394,1.004] | 1.037*** | [0.843,1.232] | -0.110 | [-0.350,0.129] | -1.144*** | [-1.291,-0.997] |
| Group (control ref.) | | | | | | | | | | |
| T2DM | -0.00757 | [-0.310,0.295] | -0.477** | [-0.835,-0.119] | -0.910*** | [-1.22,-0.598] | 0.123 | [-0.205,0.451] | 0.938*** | [0.727,1.150] |
| Time | . | | | | | | | | | |
| T1 | -0.167*** | [-0.221,-0.113] | -0.0561 | [-0.122,0.0096] | -0.101** | [-0.172,0.030] | -0.158* | [-0.3090.0066] | 0.103*** | [0.0460,0.160] |
| T2 | -0.372*** | [-0.433,-0.312] | -0.0630 | [-0.129,0.0029] | -0.120*** | [-0.187,0.053] | -0.0782 | [-0.214,0.057] | 0.254*** | [0.200,0.308] |
| Group#T1 | -0.259* | [-0.480,-0.038] | 0.0482 | [-0.248,0.344] | 0.0532 | [-0.350,0.456] | 0.300 | [-0.175,0.776] | -0.167 | [-0.414,0.0790] |
| Group#T2 | -0.0899 | [-0.339,0.160] | 0.143 | [-0.240,0.525] | -0.226 | [-0.628,0.176] | -0.0704 | [-0.538,0.397] | 0.215 | [-0.0373,0.467] |
| _cons | 3.849*** | [3.137,4.560] | -2.291*** | [-2.892,-1.690] | 0.858*** | [0.454,1.262] | -1.837*** | [-2.370,-1.303] | -1.955*** | [-2.284,-1.625] |
| *N* | 14536 | | 12007 | | 24437 | | 19984 | | 24437 | |

Alcohol consumption did not differ substantially even if group interaction became not significant (p-values 0.112). The inclusion of BMI did not alter the proportion of people who regularly engaged in some kind of physical activity across time.

### 4.4.10 Sensitivity analysis 2

The average age of the participants in the sample was more than 63 years old. Therefore, it is plausible that some of the participants received another diagnosis other than T2DM. Among the most common conditions in older age are high blood pressure and cholesterol. People affected by these conditions also often receive recommendations to change their health behaviour towards a healthier lifestyle. For this reason, people reporting a diagnosis of high cholesterol or high blood pressure were excluded from the sample. The effect of the group by time interaction at T1 for smoking became not statistically significant (model 1). Apart from this, the results did not change substantially compared to the previous models and confirmed no effect of the T2DM diagnosis on behaviour change (Table 4.23).

## Table 4-23 Results from the sensitivity analysis 2

| Model | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Behaviour | smoking | | alcohol | | Physical activity | | fruit | | Sedentary behaviour | |
| Age (year) | -0.249*** | [-0.312, -0.186] | 0.0567*** | [0.0364,0.0771] | -0.0975*** | [-0.109, -0.0864] | -0.0105* | [-0.0209, -0.0000348] | 0.0967*** | [0.0874,0.106] |
| Gender (female ref.) | | | | | | | | | | |
| Male | -0.879* | [-1.568,-0.191] | 0.581*** | [0.239,0.923] | 0.594*** | [0.412,0.776] | -0.145 | [-0.331,0.0411] | -0.870*** | [-1.035, -0.705] |
| Non pension wealth (1 lowest ref) | | | | | | | | | | |
| 2 | -3.488*** | [-4.766,-2.211] | -0.0157 | [-0.790,0.759] | 0.617*** | [0.251,0.982] | -0.252 | [-0.586,0.0813] | -0.708*** | [-1.009, -0.407] |
| 3 | -5.106*** | [-6.523,-3.690] | -0.0713 | [-0.803,0.660] | 1.277*** | [0.928,1.626] | -0.164 | [-0.482,0.154] | -1.473*** | [-1.765,-1.181] |
| 4 | -7.026*** | [-8.633,-5.418] | 0.962** | [0.254,1.670] | 1.447*** | [1.104,1.789] | -0.334* | [-0.651,-0.0174] | -1.740*** | [-2.029,-1.452] |
| 5 (highest) | -7.401*** | [-9.024,-5.779] | 2.010*** | [1.310,2.709] | 2.077*** | [1.740,2.413] | -0.0328 | [-0.338,0.272] | -2.447*** | [-2.735,-2.160] |
| Group (control ref.) | | | | | | | | | | |
| T2DM | -0.414 | [-2.172,1.344] | -1.391* | [-2.639,-0.144] | -0.810* | [-1.512,-0.108] | 0.558 | [-0.0700,1.186] | 1.435*** | [0.854,2.016] |
| Time (T0 ref) | . | | . | | | | | | | |
| T1 | -0.772*** | [-1.063,-0.481] | -0.143 | [-0.326,0.0407] | -0.108 | [-0.242,0.0261] | -0.171 | [-0.364,0.0214] | 0.201*** | [0.0908,0.312] |
| T2 | -1.570*** | [-1.868,-1.271] | -0.182* | [-0.346,-0.0177] | -0.185** | [-0.301,-0.0701] | -0.0238 | [-0.187,0.139] | 0.417*** | [0.321,0.513] |
| Group#time interaction | | | | | | | | | | |
| T2DM#T1 | -0.531 | [-2.120,1.057] | 0.515 | [-0.672,1.702] | -0.126 | [-1.037,0.786] | 0.266 | [-0.603,1.136] | -0.631 | [-1.289,0.0267] |
| T2dm#T2 | 0.755 | [-0.588,2.098] | 0.371 | [-0.752,1.493] | -0.208 | [-1.031,0.616] | -0.172 | [-0.971,0.626] | -0.139 | [-0.755,0.478] |
| _cons | 14.24*** | [9.201,19.28] | -6.010*** | [-7.517,-4.503] | 2.218*** | [1.463,2.974] | -2.464*** | [-3.222,-1.705] | -3.891*** | [-4.537,-3.245] |
| | | | | | | | | | | |
| lnsig2u | 4.252*** | [4.119,4.385] | 2.422*** | [2.278,2.566] | 1.450*** | [1.334,1.565] | 0.700*** | [0.503,0.897] | 1.503*** | [1.407,1.600] |
| *N* | 11226 | | 8338 | | 18428 | | 14706 | | 18428 | |
| *Number of groups* | 2,525 | | 1,970 | | 4,132 | | 3,398 | | 4,132 | |

### 4.4.11 Attrition Bias

A ubiquitous problem in panel data analysis is when data for a participant are missing from specific time points onwards. This issue is called dropout or attrition bias. Attrition bias was tested by conducting a logistic regression analysis.

The 19.87 % of the participants included in the sample (8.75% + 5.85% + 5.27) had monotone missingness patterns, i.e., they dropped out from the study and did not return after missing a wave table 4.24. The table reads as follows: there are in total five time points, i.e., from wave 3 to wave 7 included. For example, a pattern of 1111 (the last column) signifies that those participants took part in every wave included in this study. In total, 4894 participants were observed in all the waves.

**Table 4-24 Description of patterns of participation in the sample (1 if the participants was observed at that wave 0 otherwise).**

| Delta(wave)= 1 unit | | n = 9453 | |
|---|---|---|---|
| Span(wave)= 5 periods | | T = 5 | |
| wave: 3, 4, 5,6,7 | | | |
| | | | |
| Freq. | Percent | Cum. | Pattern |
| | | | |
| 4849 | 51.3 | 51.3 | 11111 |
| 2254 | 23.84 | 75.14 | 01111 |
| 827 | 8.75 | 83.89 | 11110 |
| 553 | 5.85 | 89.74 | 11100 |
| 498 | 5.27 | 95.01 | 01110 |
| 202 | 2.14 | 97.14 | 00111 |
| 178 | 1.88 | 99.03 | 10111 |
| 92 | 0.97 | 100 | 11101 |
| | | | |
| 9453 | 100 | | |

If the sample is restricted to those participants with complete cases for at least one behaviour, the percentage stated above is 20.47 % (9.39% + +5.99% +5.09) table 4.25.

**Table 4-25 Description of patterns of participation in the sample (1 if the participants was observed at that wave 0 otherwise). Sample restricted to those participants with at least one health behaviour in three consecutive waves.**

| Freq. | Percent | Cum. | Pattern |
|---|---|---|---|
| Delta(wave)= 1 unit | n = 7863 | | |
| Span(wave)= 5 periods | T = 5 | | |
| wave: 3, 4, 5,6,7 | | | |
| | | | |
| 4300 | 54.69 | 54.69 | 11111 |
| 1876 | 23.86 | 78.55 | 01111 |
| 738 | 9.39 | 87.93 | 11110 |
| 471 | 5.99 | 93.92 | 11100 |
| 400 | 5.09 | 99.01 | 01110 |
| 73 | 0.93 | 99.94 | 11101 |
| 3 | 0.04 | 99.97 | 10111 |
| 2 | 0.03 | 100 | 00111 |
| | | | |
| 7863 | 100 | | |

It can be hypothesised that individuals who experience T2DM are more likely to drop out. Therefore, a logistic regression analysis was performed to compare baseline data for participants who left earlier with those who remained until the end of the study Table 4.26.

**Table 4-26 Probability of attrition by T2DM group**

| Dropout | Coef. | Std. Err. | [95% Conf. Interval] | |
|---|---|---|---|---|
| | | | | |
| Age (year) | 0.052136*** | 0.00152 | 0.049157 | 0.055114 |
| Gender (female ref.) | | | | |
| Male | 0.155899*** | 0.030373 | 0.09637 | 0.215429 |
| | | | | |
| Non pension wealth (1 lowest ref>) | | | | |
| 2 | 0.014743 | 0.046169 | -0.07575 | 0.105232 |
| 3 | -0.34648*** | 0.047809 | -0.44018 | -0.25277 |
| 4 | -0.29832*** | 0.047152 | -0.39073 | -0.2059 |

| | | | | |
|---|---|---|---|---|
| 5 (highest) | -0.79089*** | 0.051145 | -0.89113 | -0.69065 |
| Group (control ref.) | | | | |
| T2DM | 0.390087*** | 0.058597 | 0.275239 | 0.504935 |
| _cons | -4.98069 | 0.112865 | -5.20191 | -4.75948 |
| | | | | |
| N = 34,879 | | | | |
| Num groups: 7863 | | | | |

Results from this table suggest the presence of attrition bias since participants from the T2DM group were more likely to drop out earlier from the study.

Also, participants who experience ill health other than T2DM could be more likely to drop out earlier from the study. For this reason, another test for attrition bias was conducted table 4.27. In this additional test participants who reported any of the seven CVD diseases (model 1), coronary heart disease (model 2) or stroke (model 3) were excluded from the sample.

**Table 4-27 Probability of dropout (any condition)**

| Model | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | dropout | 95% CIs | dropout | 95% CIs | dropout | 95% CIs |
| Age (year) | 0.0497*** | [0.0467,0.0528] | 0.051*** | [0.0453,0.057] | 0.0502*** | [0.0444,0.0560] |
| Gender (female ref.) | | | | | | |
| Male | 0.151*** | [0.0917,0.211] | 0.137* | [0.0225,0.252] | 0.142* | [0.0271,0.256] |
| Non pension wealth (1 ref.) | | | | | | |
| 2 | 0.0171 | [-0.0734,0.108] | -0.0101 | [-0.185,0.165] | -0.00089 | [-0.176,0.174] |
| 3 | -0.343*** | [-0.437, -0.249] | -0.352*** | [-0.532, -0.173] | -0.331*** | [-0.511, -0.151] |
| 4 | -0.304*** | [-0.396, -0.212] | -0.329*** | [-0.506, -0.152] | -0.309*** | [-0.487, -0.132] |
| 5 (highest) | -0.793*** | [-0.893, -0.692] | -0.823*** | [-1.014, -0.632] | -0.795*** | [-0.986, -0.603] |
| Cvd disease | | | | | | |
| (yes) | 0.254*** | [0.185,0.324] | | | | |
| Coronary heart disease | | | | | | |
| yes | | | 0.242** | [0.0678,0.415] | | |
| Stroke | | | | | | |
| yes | | | | | 0.617*** | [0.383,0.851] |
| _cons | -4.849*** | [-5.071, -4.626] | -4.581*** | [-5.005, -4.156] | -4.541*** | [-4.966, -4.116] |
| *N* | 34879 | | 7858 | | 7858 | |

## 4.5 Discussion

### 4.5.1 Summary of results

Using longitudinal panel data from the ELSA, which includes nearly 8,000 participants followed over ten years (5 waves), this research found limited evidence that the diagnosis of T2DM can trigger behaviour change in this sample of community-dwelling English older adults. Findings from the GEE and RE analysis showed that participants newly diagnosed with T2DM were less likely to be current smokers. This effect is consistent with the current literature and the paper by Hackett et al.,2018, which also showed a decrease in smoking after T2DM diagnosis. However, the T2DM and control group differed in terms of baseline characteristics, as described in the section on descriptive characteristics. Therefore, the effect detected on smoking could have been a result of these groups being different rather than a genuine effect of the T2DM diagnosis on the probability of smoking. Once these characteristics were balanced between the two groups with the PSM approach, the effect on smoking was not detected anymore, and even putting that aside, the effect on smoking is not sustained. However, it is essential to acknowledge that it is difficult to determine if the lack of effect of the T2DM diagnosis on smoking in the PSM sample was genuine or simply due to a decrease in statistical power given the smaller size of the matched sample compared to the one employed in the previous GEE or RE analysis. Nevertheless, the impact of T2DM diagnosis on behaviour change was found to be minimal.

The results from the replication analysis (GEE model) match those from the Hackett study. Apart from the effect of the time by group interaction at T1 mentioned above, similarly to Hackett et al., 2018 the current analysis found an effect of time independent of group for smoking (see for example the coefficients

of T1 and T2 respectively in table 4.5) but no effect of group independent of time. The results from alcohol did not show any effect of the group by time interaction but a significant effect of group and time alone (table 4.8) as was the case of the previous study by Hackett. It is worth noting that in the current analysis the effect of time was only significant at T2 but not at T1. Except for the group effect, which was significant in the present analysis (table 4.11), e.g., the T2DM group consistently showed a lower level of physical activity compared to the control but not in the Hackett et al., 2018, the results for physical activity are also matching and highlight a significant effect of time e.g., levels of physical activity are generally decreasing at the 3-time points and a non-significant group by time interaction. Results for sedentary behaviour are concordant with the previous study and report a significant effect of time, which shows an increase of sedentary behaviour over time independent of groups (table 4.14), a significant effect of the group variable that highlighted that people from the T2DM were more likely to report sedentary behaviour and a non-significant group by time interaction. For fruit and vegetable consumption, the overall group difference was not significant, while an effect of time was detected as was the case of Hackett et al., 2018. The present analysis did not find any effect for the group by time interaction, whereas in the previous study, this interaction was borderline significant (p-value <0.10).

In all three analyses, the effect of the other covariates appears consistent with the findings from part of the previous literature on the topic of behaviour change. Smoking propensity declines with increased education and age. This is consistent with the observation that differentials in diabetes management capabilities are highly responsive to the socioeconomic gradient. In line with Grossman's model theoretical predictions, education and disposable income were associated with greater chances of investing in health irrespective of T2DM

diagnosis. Participants with a high-school certificate were less likely to be current smoker and to report sedentary behaviour but more likely of being physically active compared to the participants with no educational qualification. A comparable effect in terms of the magnitude and statistical significance of the coefficients can be observed among the participants in possession of a college degree always compared to the participants with no educational qualification.

### 4.5.2 Findings in the context of the broader literature

The overall findings from the current analysis are consistent with the previous literature documenting a reduction in smoking after individuals were diagnosed with T2DM [131, 135, 136]. In this sense, the results in this thesis add to the current literature by corroborating these positive changes in smoking habits by using an extended follow-up period and a more robust methodology that accommodated individual-level heterogeneity in response to T2DM more thoroughly than previous studies did [32]. Furthermore, this is one of the relatively few research to investigate changes in physical activity following a T2DM diagnosis both in the UK and Europe since previous research which looked at changes among this health behaviour was based in North America, Canada [135] and the US, respectively [49].

### 4.5.3 Strength and limitations

The research incorporates longitudinal panel data covering twelve years, which allowed the evaluation of multiple health behaviour with a more extended follow-up than most studies in this area. In addition, it uses three different methodologies to answer the same research question. One of these methodologies is the first to account for individuals' level unobserved heterogeneity in response to T2DM diagnosis and estimate its effect via the intraclass correlation *rho*.

Nonetheless, several limitations must be acknowledged. First, due to different methodologies employed during this research, sample sizes across all the analyses were (PSM approach) different in some instances, which may partly drive the observed results. Second, the diagnosis is self-reported; therefore, participants may forget to mention the diagnosis of T2DM during a specific wave and remember it during consequent waves. If this is the case, participants newly diagnosed with T2DM may change their short-term behaviour, but this effect may vanish before the next wave, and no effect may be observed. This would have influenced the current results by reducing the effect size observed. Third, occasions (waves) are two years apart; therefore, participants can be diagnosed soon after the previous waves. This might be particularly the case during the waves where a concomitant nurse visit took place alongside the main questionnaire because the blood sample may detect the raised level of HbA1c (as can be seen from the descriptive statistics presented in Table 4.3 where the T2DM group had average HbA1c values above the cut-off of 6.5%, but they did not yet report a diagnosis of T2DM). Again, this may have contributed to reducing the observed effect size because participants may only change their short-term behaviour. This effect would be consistent with part of the literature cited in the introduction, which shows that behaviour change did not persist in the long term [32, 49]. Fourth, we have no information on whether participants received advice or education from a health professional following a T2DM diagnosis in line with the recommendation suggested by the guidelines. Fifth, as is often the case in many longitudinal studies, the current analysis suffers from attrition. Older participants were more likely to drop out earlier from the study, while the opposite was observed for individuals from the highest non-pension wealth quintile. Moreover, participants with certain health conditions, such as T2DM or CVD

diseases, were also more likely to withdraw from the study earlier compared to other participants who did not experience the same conditions. Two potential reasons for concern could results from attrition. Firstly, the sample size may be reduced considerably, negatively affecting the statistical power. Secondly, attrition can lead to non-response bias. While using maximum likelihood retains consistency if data are missing at MAR and thus it allows the researcher to keep the original sample size; it is not possible to rule out with complete certainty that the issue of non-response bias affected the current analysis. However, the ELSA benefitted from several refreshment samples at waves 3,4, 6 and 7, where new participants were recruited to counterbalance the fact that older participants were more likely to drop out. Concerning non-pension wealth, the primary analysis indicates that people from the highest wealth quintile are less likely to conduct a sedentary lifestyle and more likely to be physically active. This finding provides a reasonable degree of reassurance that the potential bias introduced by attrition should not be a significant concern given that present research found limited evidence of behaviour change following a T2DM diagnosis. It is also worth noting that while more sophisticated statistical techniques, such as inverse probability weighting, could be considered in future studies, the issue of attrition does not represent a cause of major concern in the specific context of this research. The present analysis aimed to complement the findings from randomized controlled trials (RCTs), which indicated that individuals modify their behaviour after being diagnosed with T2DM. Therefore, an intention-to-treat analysis was performed to make the results more comparable with the ones from RCTs, as they usually also perform an intention-to-treat analysis. To conclude, despite trying to be as comprehensive as possible, the literature review presented in the introduction was not systematic, and some relevant studies might have been missed.

### 4.5.4 Implication for policy and practice

Randomized experiments and translational intervention are effective in promoting behaviour change. The present research, however, could not replicate these findings at a population level, e.g., outside of these targeted interventions to promote behaviour change. Conversely, it provides robust evidence that the behaviour change is challenging to achieve by the patients newly diagnosed with T2DM. Therefore, it highlights the need to understand how to motivate and support people to accomplish the necessary behavioural adjustments in line with the recommendations for optimal T2DM management. Previous research has found that when new diagnosis information is combined with further medical intervention, e.g. further examination or medical advice, positive behavioural responses are observed among individuals with T2DM[49] [48]. This might be particularly beneficial for underserved populations that may lack the knowledge about the potential adverse health consequences of unhealthy behaviour.

### 4.5.5 Further research

Previous literature could not reach a firm conclusion on whether the new T2DM diagnosis information or the likely additional medical interventions enabled behaviour change. A crucial aspect that could not be addressed in the current research due to limited data availability. Therefore, further research looking to disentangle these two distinct effects would be particularly beneficial and potentially increase the marginal benefit of large screening programmes for T2DM. In the UK, it is recommended that people newly diagnosed with T2DM be referred to structured diabetes patient education programme because there is evidence that these programmes positive affects behaviour change. There have also been large-scale incentive schemes such as the QOF, which included T2DM indicators and have shown positive effects on achieving the NICE care processes

and treatment targets [17]. However, despite these nationwide initiatives aimed at improving T2DM management (and outcomes), the proportion of people with inadequate levels of physical activity, high sedentary behaviour and minimal fruit and vegetable consumption remains high. This may be due to geographical variations in the implementation of processes of T2DM in primary care, an aspect which deserves further investigation. To conclude, this research shows that people from the lowest wealth quintile and less educated are less likely to invest in their health. Often these people live in the most deprived areas which also have health hazards such as high concentrations of fast foods, tobacco shops, off licences, and the absence of adequate green spaces which may act as a barrier to physical activity with the potential to exacerbate inequalities further. Additional research on the relationship between neighbourhood characteristics and behaviour change is warranted.

### 4.5.6 Conclusions

The present investigation found limited evidence that T2DM diagnosis could trigger health investment as defined by the Grossman model for the demand for health. Findings clearly showed that behaviour change is challenging to achieve at the population level outside of RCTs and targeted translational intervention which showed promising results in this direction. Nevertheless, these findings may contribute to advancing the discussion on behaviour change by signalling the need to educate and encourage people with T2DM to acquire the necessary skills to manage their condition better. This is especially crucial for people from the lowest wealth quintile, as indicated by the strong effect of income on the probability of conducting a healthy lifestyle regardless of having been diagnosed with T2DM.

# Chapter 5
# Discussion

The prevalence of type 2 diabetes (T2DM) has steadily increased over the past few decades [4, 152-154]. Uncontrolled T2DM can have a more than detrimental effect on the quality of life of people living with this condition [7] and lead to increased healthcare utilisation[52], such as hospital admission and GP use [155]. People with T2DM are at greater risk of being hospitalised, particularly in middle-aged populations like the one represented in this thesis where the odds of being admitted to a hospital over a lifetime can be up to six times higher than the general population [156]. Furthermore, recent data shows considerably higher both COVID-19 related mortality rates [Odds ratio 2.03 (95% CI; 1.97-2.09)] and risk of intensive care unit (ICU) admission [Odds ratio 2.21(95%CI; 0.88-5.570] amongst the people with T2DM compared to people without T2DM [157]. Last but not least, treatment and prevention of T2DM are estimated to be 10 per cent of the total NHS budget for England and Wales [126]. Comparable figures, if not higher, can be observed in Europe (France, Italy, Germany, Spain, Sweden, Belgium and the Netherlands) and worldwide (Australia, Canada, Taiwan), with the United States (US) standing out as having exceptionally high cost [158-160].

Several risk factors related to T2DM management are amenable to change [145, 161]. For example, some adverse consequences of T2DM derive from the risk of incurring both macrovascular and microvascular complications. These risks can be controlled by the people living with T2DM by adopting a healthy lifestyle, regularly monitoring critical biomarkers and adherence to medication [31, 162]. Therefore, guidelines are in place to help people with diabetes to better manage their condition [44]. However, despite the overwhelming evidence showing the

benefit of following the guidelines regarding the reduced risk of experiencing complications and improved quality of life, adherence to these guidelines is not always mastered by people living with T2DM[31, 163]. As a result, adherence to self-care behaviour is suboptimal in the UK and globally [164]. As shown in chapter 2, not all the people adhere to the bundle of health checks for T2DM management recommended by the national guidelines [165].

The present thesis investigated some of the most pressing issues related to T2DM management from a health economic perspective[166]. This purpose was achieved using the Grossman Model of the Demand for Health as the underlying theoretical framework throughout the entire work. According to this model, rational economic agents should adhere to the guidelines and invest in health-protective behaviour, adjusting their habits to maximise their lifetime utility. Examples of this behaviour are regularly attending medical checks for T2DM, quitting smoking, and adopting a healthy diet. However, deviation from this utility maximising behaviour is consistently seen in the empirical literature surrounding the management of T2DM [19, 26, 28], and adherence to T2DM guidelines is heterogeneous. Analysis 1 postulated that individuals' differences in time and risk preferences might partly explain this heterogeneity. Analysis 2, instead, building upon the findings of analysis 1, analysed how this heterogeneity in time and risk preferences might impact long term outcomes and cost using a detailed disease progression model, namely the UKPDS. Finally, to complete, analysis 3 investigated whether the health information of T2DM diagnosis represents a sufficient *'health shock'* able to trigger behaviour change in newly diagnosed ELSA participants. The following section will provide a more elaborate description of each analysis along with the main findings and implications from the complete empirical inquiry.

## 5.1 Analysis 1

The first analysis of this thesis investigated the association between time and risk preferences and adherence to the medical check for type 2 diabetes T2DM management suggested by the national guidelines. As described in chapter 1, the guidelines suggest a bundle of medical checks that people with T2DM should adhere to annually. It was hypothesised that the heterogeneity in individuals' time and risk preferences might partly explain differences in adherence to these guidelines. This hypothesis was tested within a Grossman framework, according to which adherence to medical checks represents an investment in health. A natural consequence of the Grossman model would be that rational economic agents are expected to invest in their health and, consequently, to comply with the NICE guidelines on diabetes management. However, observed behaviour appears to deviate consistently from the behaviour that the traditional economic theory would predict, e.g. rational, forward-looking decision making [63, 167]. In addition, there is a great deal of heterogeneity in the way people living with T2DM manage their condition, which has not yet convincingly been explained by the 'classic' socio-demographic factors such as age, gender, education and income[54]. In this sense, time and risk preferences have already been considered a relevant component of the unobserved heterogeneity related to uncontrolled diabetes [52]. The analysis provides a two-fold contribution to the existing literature. Firstly, it would explain why adherence to T2DM management is not always in line with recommendations suggested by NICE guidelines for optimal T2DM management. Secondly, it sheds light on the degree of heterogeneity observed in adherence to T2DM management. In addition, since T2DM is partly a lifestyle-related condition, a better understanding of the critical drivers for optimal diabetes management, especially those beyond the 'classic'

sociodemographic risk factors, could bring valuable insights into how to target interventions to increase adherence to the T2DM management. A theme that has recently become a cornerstone topic in many countries' political agendas. Unpack what works for whom and under what circumstances is crucial to inform policymakers on designing interventions to empower people with T2DM to manage their condition better. As pointed out by many authoritative sources, there is no universal treatment for everyone. Despite the clear theoretical link between time and risk preferences and health investment, results from the first analysis found no significant association between these variables and adherence to the T2DM recommended care processes. However, these findings need to be interpreted with caution. Several studies found an association between preferences and adherence [19, 28]. Therefore, the lack of association ascertained in this context might be partly due to the small sample size and the subsequent lack of statistical power rather than a genuine absence of any relationship between these two variables. However further analysis and sensitivity checks which increased the statistical power considerably still found no statistically significant effect of time and risk preference on adherence to the medical checks for T2DM management. To conclude, even if cases with no association between preference and adherence are less frequent, they can still be found in the literature [27]. Thus, despite time and risk, preferences might represent a promising framework to increase adherence to the guidelines for an optimal T2DM management, findings from the current research could not corroborate this hypothesis further using data from a sample of community-dwelling older people from the ELSA.

## 5.2 Analysis 2

Building upon analysis 1, analysis 2 estimated the long terms health outcomes (and cost) of the people living with T2DM according to the level of their risk and preferences. However, firstly I reviewed the current economic models for type 2 diabetes. Among 29 models identified based on seven criteria developed explicitly for the purpose and described in the dedicated section 3.2, the UKPDS was chosen as the most suitable tool for calculating the long-term outcomes of patients living with T2DM according to the available data. The UKPDS was populated with individual-level information from the same cohort employed in the first analysis. More in detail, individual-level data on a rich set of biomarkers from the ELSA nurse module, in addition to the sociodemographic information contained in the main questionnaire of the same dataset. Then, using a novel approach represented by the unique availability of data on risks and time preferences collected through a laboratory experiment during wave 5 of the ELSA, these model inputs were stratified by participants' attitudes towards risk and delayed gratification, e.g., time and risk preferences. Therefore, the impact of time and risk preferences on T2DM long-term outcomes and cost were calculated via this two-step approach, expressly by postulating that people with different values for time and risk preferences might also have different mean values of the UKPDS relevant variables. Subsequently, by inputting these different sets of values into the UKDPS, the impact of preferences on costs and utilities was calculated. To my best knowledge, this is the first study to use a detailed disease progression model to calculate the long-term health outcomes of patients with T2DM based on the level of their time and risk preferences using a UK population.

It was hypothesised that participants with low time preference rates be more likely to engage in self-protective behaviour since they could be more willing to decline

present utility for a greater reward in the longer term, e.g., quitting smoking or following a healthy diet, compared to people who discount future events more heavily, e.g., high discount rate, and do not value future utility in the same way. A similar hypothesis was tested for risk preferences. Risk-averse participants were postulated to be possibly more aware of the complications which may arise from T2DM and, therefore pay more attention to the recommendations suggested by the guidelines for T2DM management than their more risk-tolerant counterparts. However, the current study's results indicate no difference in T2DM-associated health outcomes and costs between the two groups of participants, who differed in their time preference rates. Additionally, the study findings revealed that the participant's risk attitude did not impact the results.

## 5.3 Analysis 3

In analysis 3, I investigated whether the *'health shock'* of T2DM diagnosis increases participants investment in health in the way defined by the Grossman model. More in detail, the model makes several predictions. First, considering that the health stock may depreciate faster as people age (given a relatively inelastic demand curve for health), individuals would desire to offset this change by increasing the level of investment in their health as they age. Consequently, they will buy more medical goods, increase health activities, or both [35]. Second, it also predicts that education should increase investment in health, such as the more educated individuals would demand a more extensive optimal stock of health. Third, high-wage individuals will invest more in health by spending on medical goods and services rather their own time relatively to low-wage individuals since the cost of time is relatively higher for them. Results found limited evidence of increased investments in health by the ELSA participants who self-reported a new T2DM diagnosis. Out of the three models employed during

analysis, only moderate evidence of behaviour changes after T2DM diagnosis, e.g., decreased smoking was detected. Nevertheless, education pointed in the hypothesized direction with the more educated participants more likely to be physically active and less likely to smoke and to conduct a sedentary lifestyle.

The study represents a few longitudinal analyses on behaviour change that attempted to accommodate the correlation among repeated measurements within the same subject using a more sophisticated approach than most previous analyses in this area attempted to achieve. Previous research accommodated intra-subjects correlation across different occasions but achieved that by using marginal modelling in the form of GEE. This is a popular approach but reflects population-averaged effects and might be a less sensitive modelling approach. In particular, mixed models are preferred if the individual specific effect is of interest rather than the overall treatment effect, like in the case of the present analysis.

Several consequences emerge from this analysis. Firstly, behaviour change is often difficult to achieve, especially outside the targeted intervention aimed explicitly for this purpose, whether randomized experiments or translational interventions. Second, it appears that the information of TD2M diagnosis is not sufficient to trigger behaviour change. Undoubtedly the GEE and RE models found changes in people who recently reported a diagnosis. However, the effect size was moderate and probably insufficient to significantly reduce the risk of incurring T2DM related complications, as previous research suggests “Knowing it is not half of the battle” [47]. Conversely, the evidence suggests that behaviour change is more apparent when a new T2DM diagnosis is accompanied by further medical advice or structured education on managing the condition. Hence the need to empower people living with T2DM with the necessary information to

manage their condition better. This is especially important amongst the most underserved population, which often lack knowledge on the importance of T2DM management skills. As highlighted by the findings of this analysis, the more educated people and people from the higher income quintile had greater likelihood of changing behaviour, irrespectively of the T2DM diagnosis.

Finally, the present analysis also highlights the importance of early detection of T2DM as an overwhelming evidence base across different disciplines also suggests. At present, there are more than half of a million cases of undiagnosed T2DM only in the UK. Moreover, suppose people change behaviour due to the diagnosis of T2DM, especially when coupled with further medical advice, as the current analysis implies to some extent. In that case, timely detection of T2DM alone represents a unique opportunity to improve patients' outcomes at a relatively low cost. Secondly, suppose people change behaviour because of the T2DM diagnosis. In that case, it might also be the case that the pre-diagnosis of T2DM or at-risk status may trigger behaviour change, which needs further exploration. A recent integrative review on the topic suggests that this might be the case if adequate support to motivate lifestyle change is provided to the people newly diagnosed with pre-diabetes [168]. A possible way to achieve an earlier diagnosis is to increase screening for T2DM. Diabetes has a latent, asymptomatic period where the condition is not manifested but can already be detected. As a result, a substantial proportion of the new cases of T2DM are detected because complications are already manifesting. These complications could potentially be avoided with an earlier diagnosis of the condition. The Addition trial, which showed that early detection and treatment of T2DM reduce cardiovascular morbidity and mortality, also found that the timing of the treatment for blood pressure, cholesterol, and HbA1c is more important than its intensity[169].

Therefore, reducing the time between when the condition is already manifesting and when the condition is detected would accrue significant benefit [170]. Large scale screening programmes have already brought promising results in this direction, as evidenced by a recent trial from Korea [47]. Another way to promote early detection of the condition would be opportunistic screening, e.g., checking for T2DM even if there are no symptoms. Still, there is the chance to contact the patient for other reasons; for example, a routine visit to the GP or the dentist for a general check-up has been proven to improve the timely detection of T2DM significantly.

Timely diagnosis is of particular salience for an older adult population since they represent the age category with the highest prevalence of T2DM. They are also more likely to have comorbidities, resulting in the diabetes treatment being more complex due to polypharmacy and acquired unresponsiveness to certain generic medications that are routinely used to treat other conditions rather than T2DM. For example, metformin may be administered to prevent cardiovascular diseases. However, increased tolerance to the medication may develop through the years and make metformin not a valid option to treat T2DM. Therefore, behaviour change is of particular importance to this age group. Surprisingly there is a lack of empirical evidence that focuses on behaviour change for this specific age group.

Furthermore, the available evidence derives in several cases from controlled experiments such as RCT [171]. This opens two crucial considerations. First, depending on trial design and implementation, in certain occurrences, people who enter trials or voluntarily participate in targeted programmes aimed at changing behaviour are a selected population who are likely to have attempted to change behaviour repeatedly. Therefore, it is perhaps not surprising the

relatively limited evidence on behaviour change pertains to these types of studies. In addition to that, any behaviour change observed in a partly self-selected population may not necessarily inform the behaviour change among the general population. Hence, it may be not easy to test any predictions from the economic theory based on this kind of data. On the other hand, the present study uses information from a large representative sample of the English populations, and thus its findings are generalizable to a broader population.

One of the limitations found in this last empirical analysis is the 'self-reporting nature of the diagnosis and the impossibility to disentangle the effect of the information from the effect of the recommendations following the diagnosis. Another limitation is that initial changes were measured, and there is no proof that these observed behaviour changes will persist in the long term. Nonetheless, long-term changes initially require short-term changes.

To conclude, an important final limitation that needs to be acknowledged is that this work focused exclusively on the demand side influences that may affect the management of T2DM. Albeit this represents an essential factor that needs to be considered, there might be supply influences deemed to influence the adherence to the guidelines for managing T2DM. Over the past years, the NHS has gone through several organisational reforms that have affected healthcare services delivery. These reforms are likely to have impacted providers' behaviour in aspects of relevance for this thesis. Of particular interest is the Quality Outcome Framework (QOF): a pay-for-performance incentive scheme for non-salaried GPs in the UK and financial reward linked to achieving the pre-determined target on various key quality indicators. The scheme was first introduced in 2004 and involved more than 100 quality indicators related to routine care processes for common chronic conditions, including several T2DM indicators. Quality indicators

for blood pressure, cholesterol and HbA1c, for example, were removed during April 2011. The main disadvantage of these pay for performance schemes has been extensively documented in the literature, often referred to as the ‘ratchet effect’. Since providers, in this case, represented by GPs, might anticipate the discontinuation of the scheme, the incentives to improve is weakened, and the attainment of quality may fall to levels comparable to the pre-scheme period. The evidence on how this effect may impact providers’ behaviour, in general, is mixed. While specific indicators have been affected, a study focused on the impact of QOF on the care processes for monitoring blood pressure, HbA1c and cholesterol found no substantial differences in the achievement of these targets after the program's discontinuation. However, local healthcare providers exited the QOF at different times, and locally focused alternatives to the scheme were established. This might partly explain the variation observed in the level of achievement in the target for blood pressure, cholesterol and hba1c at the national level.

## 5.4 Conclusions

Adherence to guidelines is crucial for diabetes management and preventing microvascular and macrovascular complications. Furthermore, good T2DM management skills are essential for the elderly, where the prevalence of T2DM is significantly higher than in the general population. However, sub-optimal adherence and uncontrolled T2DM are among the most significant challenges that healthcare systems are experiencing globally. These issues cannot be ignored both for their detrimental effect on people's quality of life and the additional pressure on the sustainability of the healthcare system. By encompassing three different analyses, the present thesis contributes to advancing the discussion on improving adherence to T2DM management

guidelines and helping people with T2DM acquire the necessary skills to live a happy and fulfilling life.

## 5.5 Key priorities for future research in this area

This concluding section discusses key priorities for future research in the field of type 2 diabetes management from a health economics perspective that has emerged from the three analyses conducted in this thesis. In the second analysis, it was suggested that individuals with high time preference rates, who tend to prioritise the present over the future, may be less inclined to invest in their health by attending medical check-ups. However, further research is needed to determine whether present bias specifically, rather than variations in time preference, could be a predictor of suboptimal adherence to T2DM diabetes management guidelines. Unfortunately, due to time constraints, this was not explored in the present thesis. Nonetheless, exploring this avenue could yield valuable insights for advancing the discussion on increasing adherence. Of particular interest would be differentiating between sophisticated and naïve present-biased individuals. While the former is aware they are present biased and can anticipate that behaving in a time-consistent manner will be challenging, the latter do not realise they are present biased and expect to follow through with their plans. Therefore, sophisticated present biased individuals should be more responsive to strategies to overcome present biasedness such as commitment devices in the form of deposit contracts. Another potentially fruitful area for future research, which also emerged from Chapter 2, would be to explore the degree of temporal stability of time and risk preference by comparing people's attitudes towards risk and delayed gratification at different points in time by using ideally both incentivised and non-incentivised measures for preferences. If measures for preferences were available at different time points this would open the possibility

of using more sophisticated econometric techniques to the analysis of longitudinal data which will contribute to the discussion on whether preference are endogenously or exogenously determined. The analysis conducted in Chapter 2 had several limitations some of which were directly related to the available data. Firstly, data on preferences were collected only for a relatively small subsample of the ELSA participants, an aspect which constrained statistical power and limited the range of methodologies that could have been applied to the data. This has also limited the type of disease areas that could have been investigated. Secondly, the time horizon between the smaller sooner reward and the later greater reward was a maximum of two months. This time period is probably too short to capture the relationship between preferences and the insurgence of T2DM-related long-term complications. Therefore, considering this limitation, a direction for future work could be to collect measures for time and risk preferences on a larger scale. For example, the UK has recently launched the creation of 'Future Health', a large new scale healthcare dataset involving 5 million people to improve disease prevention. Including measures for preferences in the form of survey questions or incentivised choice tasks would be especially beneficial to advance the knowledge on how improve prevention and treatment of prevalent conditions such as T2DM and more generally healthy risky behaviour. Given how the present research was conducted also analysis 3 employed a limited sample size. However, it revealed that using a detailed disease progression model applied to data on risk and time preference is a novel approach and represents an area which warrants further investigation. To conclude, as a result of the last analysis it emerged that behaviour change is challenging to achieve. This finding highlighted the need to understand better the individuals' characteristics associated with a greater chance to succeed in

changing behaviour towards a healthier lifestyle. Further investigation should be undertaken to study the relationship between preference and behaviour change.

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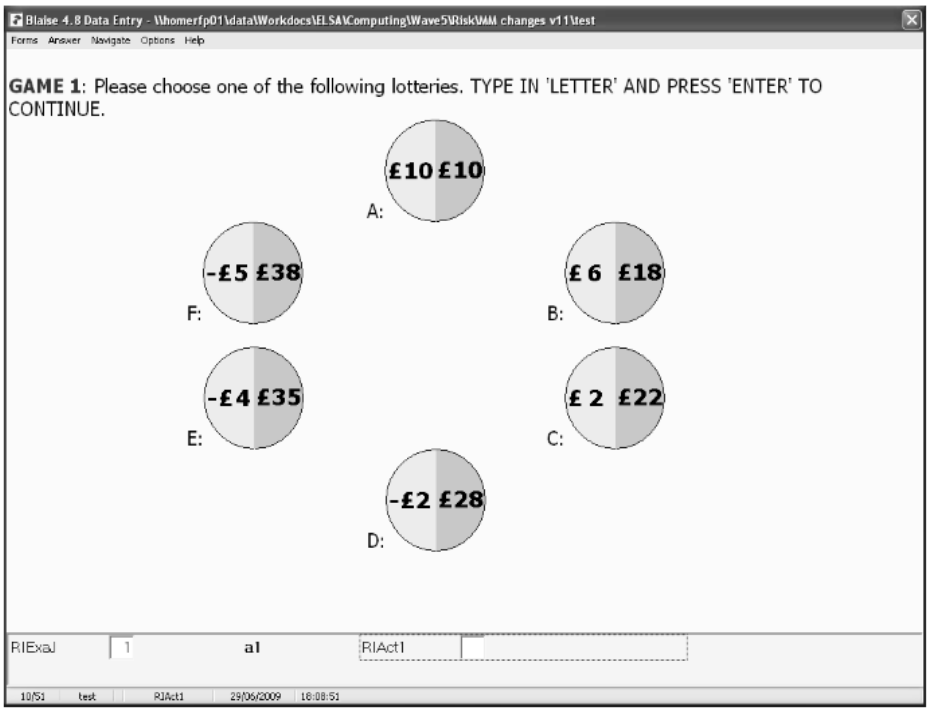
## Appendix A

## A.1 Example of a representative risk preference task (game 1)




## A.2 Example of a representative time preference task

**A.3 Regression results (Odds Ratios and 95% CIs) for the shorter time trade-off as a measure for time preferences. The dependent variables are HbA1c, blood pressure and feet check respectively.**

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Hab1c check | | Hab1c check | | Hab1c check | | Hab1c check | |
| Hab1c check | | | | | | | | |
| 50-70 (ref.) | | | | | | | | |
| >70 | 1.940 | [0.655,5.749] | 2.001 | [0.670,5.976] | 1.795 | [0.599,5.384] | 1.859 | [0.614,5.631] |
| Male (ref.) | | | | | | | | |
| Female | 0.505 | [0.196,1.302] | 0.485 | [0.186,1.264] | 0.532 | [0.204,1.386] | 0.513 | [0.195,1.348] |
| Time preference (low discount rates ref.) | | | | | | | | |
| High discount rate | | | 1.558 | [0.614,3.951] | | | 1.503 | [0.585,3.860] |
| Risk-averse (ref.) | | | | | | | | |
| Risk-neutral | | | | | 0.590 | [0.123,2.829] | 0.641 | [0.130,3.153] |
| Risk-lovers | | | | | 0.521 | [0.143,1.900] | 0.531 | [0.145,1.941] |
| Observations | 93 | | 93 | | 93 | | 93 | |
| Pseudo $R^2$ | 0.026 | | 0.034 | | 0.037 | | 0.044 | |
| *AIC* | 113.3 | | 114.4 | | 116.1 | | 117.4 | |
| *BIC* | 120.9 | | 124.6 | | 128.8 | | 132.6 | |

Exponentiated coefficients; 95% confidence intervals in brackets

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Blood pressure check | | Blood pressure check | | Blood pressure check | | Blood pressure check | |
| Age | | | | | | | | |
| 50-70 (ref.) | | | | | | | | |
| >70 | 5.022 | [0.268,94.19] | 5.275 | [0.281,99.16] | 5.707 | [0.298,109.1] | 6.327 | [0.327,122.3] |
| Male (ref.) | | | | | | | | |
| Female | 2.382 | [0.365,15.52] | 2.254 | [0.346,14.67] | 2.021 | [0.309,13.20] | 1.878 | [0.288,12.25] |
| Time preference (low discount rates ref.) | | | | | | | | |
| High discount rate | | | 2.139 | [0.420,10.88] | | | 2.482 | [0.479,12.87] |
| Risk-averse (ref.) | | | | | | | | |
| Risk-neutral | | | | | 2.089 | [0.106,41.20] | 2.778 | [0.134,57.67] |
| Risk-lovers | | | | | 2.393 | [0.122,46.83] | 2.547 | [0.129,50.34] |
| Observations | 93 | | 93 | | 93 | | 93 | |
| Pseudo $R^2$ | | | | | | | | |
| *AIC* | 44.68 | | 45.31 | | 48.92 | | 49.12 | |
| *BIC* | 52.28 | | 55.44 | | 61.58 | | 64.32 | |

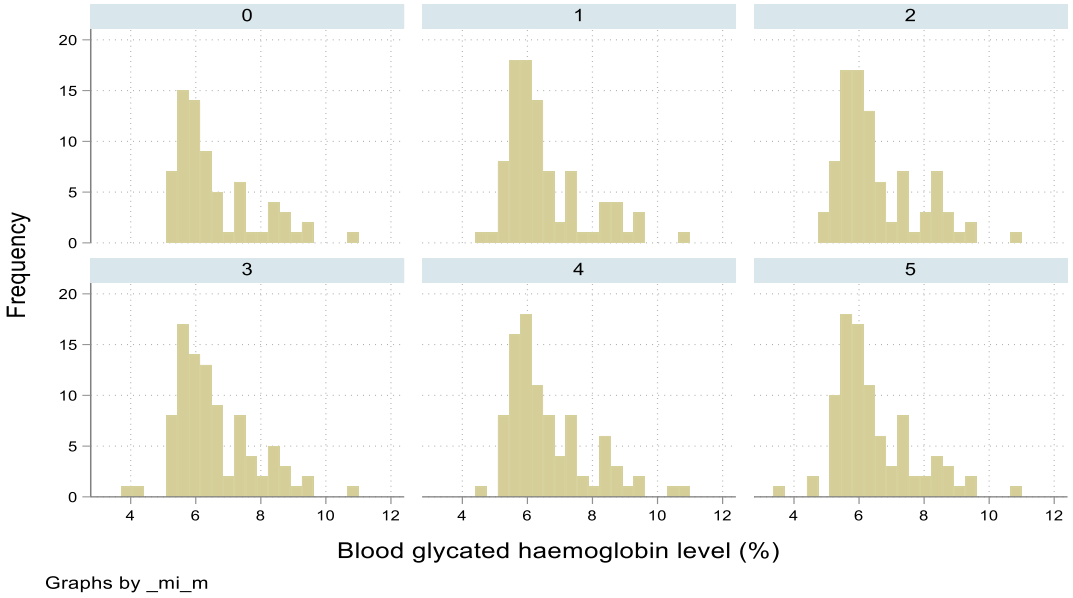
Exponentiated coefficients; 95% confidence intervals in brackets

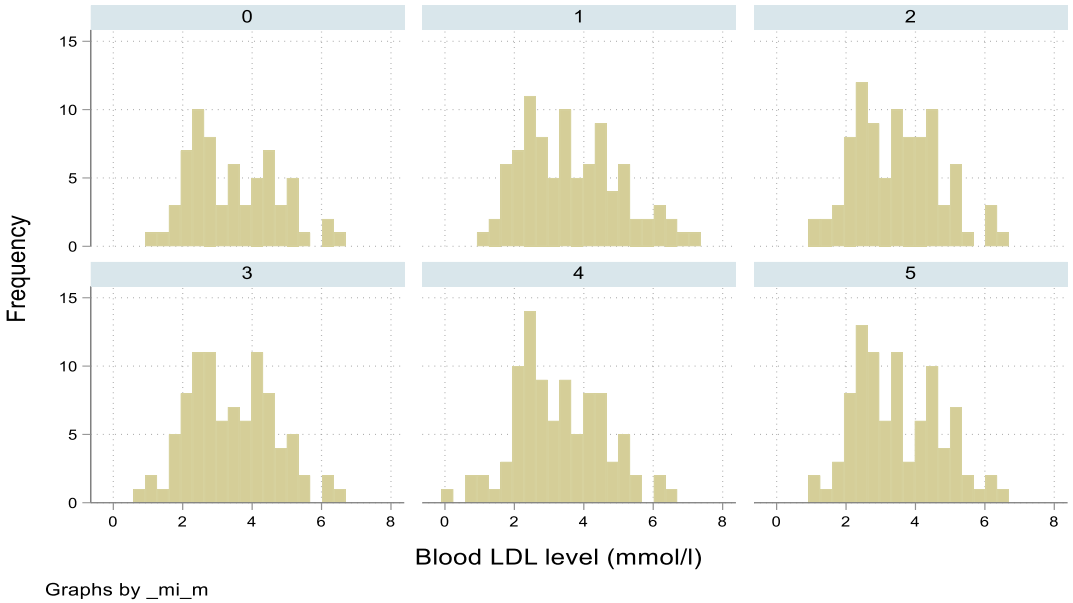
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

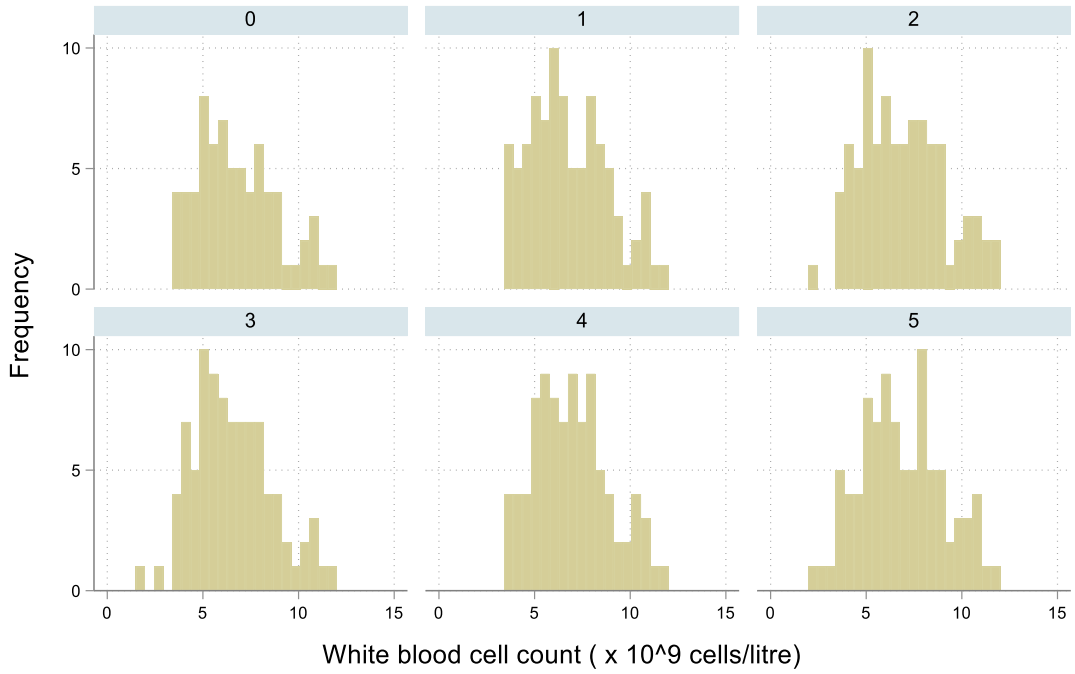
| Model | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Feet check | | Feet check | | Feet check | | Feet check | |
| Feet check | | | | | | | | |
| 50-70 (ref.) | | | | | | | | |
| >70 | 1.652 | [0.554,4.922] | 1.734 | [0.574,5.243] | 1.583 | [0.522,4.795] | 1.698 | [0.549,5.258] |
| Male (ref.) | | | | | | | | |
| Female | 0.522 | [0.198,1.371] | 0.489 | [0.183,1.308] | 0.556 | [0.209,1.479] | 0.518 | [0.191,1.402] |
| Time preference (low discount ref.) | | | | | | | | |
| High discount rates | | | 1.969 | [0.753,5.150] | | | 1.983 | [0.746,5.273] |
| Risk-averse (ref.) | | | | | | | | |
| Risk-neutral | | | | | 0.978 | [0.174,5.486] | 1.138 | [0.194,6.664] |
| Risk-lovers | | | | | 0.476 | [0.131,1.738] | 0.488 | [0.132,1.800] |
| Observations | 93 | | 93 | | 93 | | 93 | |
| Pseudo $R^2$ | 0.020 | | 0.039 | | 0.032 | | 0.050 | |
| *AIC* | 110.0 | | 110.1 | | 112.8 | | 112.9 | |
| *BIC* | 117.6 | | 120.2 | | 125.5 | | 128.1 | |

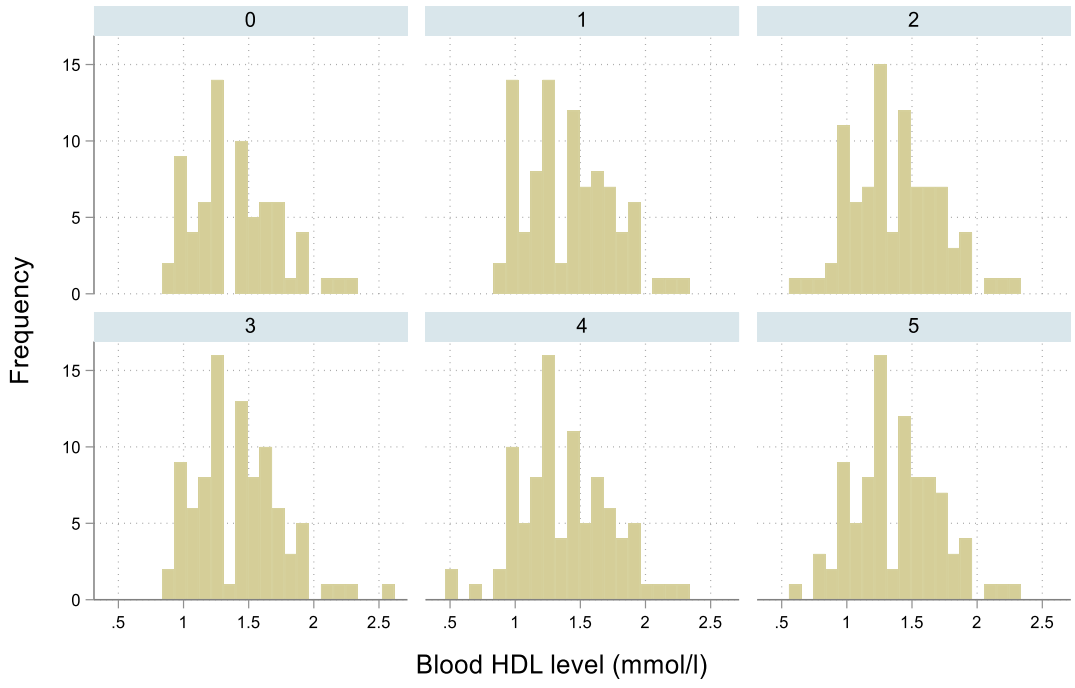
Exponentiated coefficients; 95% confidence intervals in brackets
* p < 0.05, ** p < 0.01, *** p < 0.001

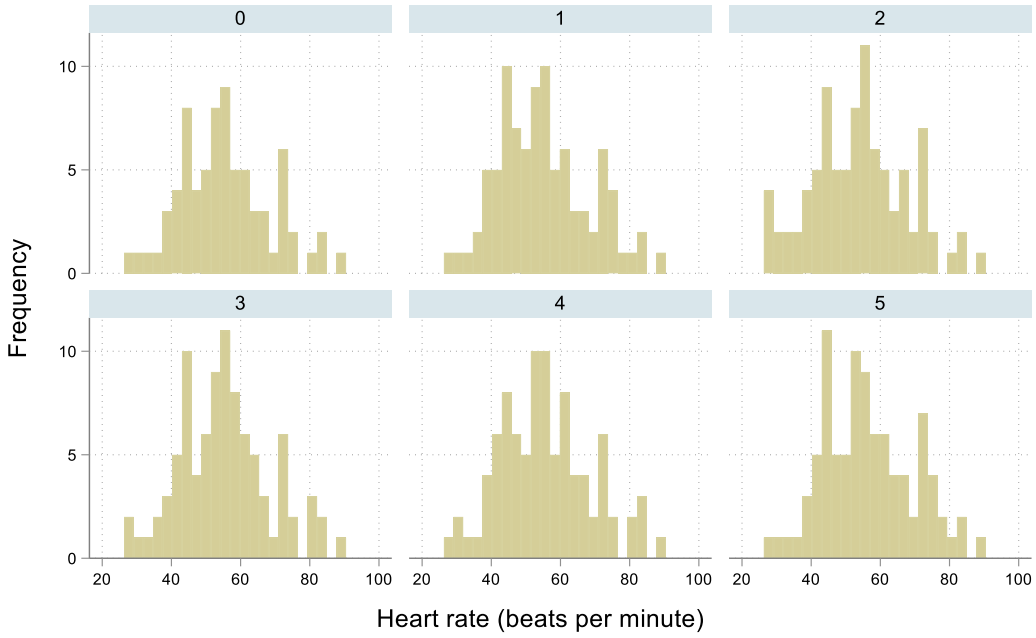
## Appendix B1


0
1
2
3
4
5
Frequency
Blood glycated haemoglobin level (%)
Graphs by _mi_m

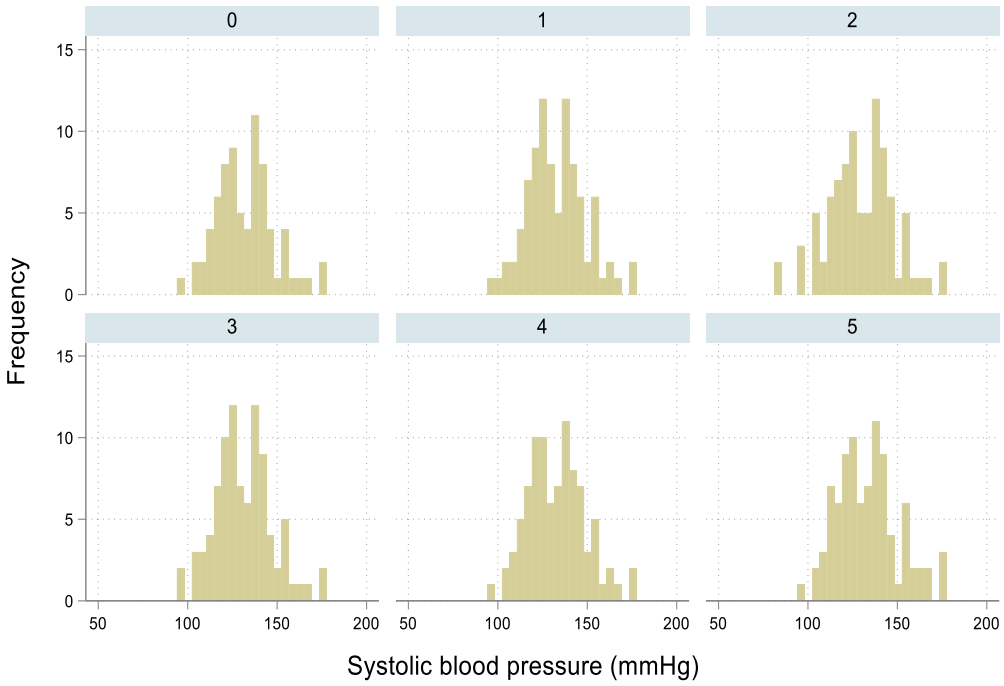

0
1
2
3
4
5
Frequency
Blood LDL level (mmol/l)
Graphs by _mi_m


0
1
2
3
4
5
Frequency
White blood cell count ( x 10^9 cells/litre)
Graphs by _mi_m

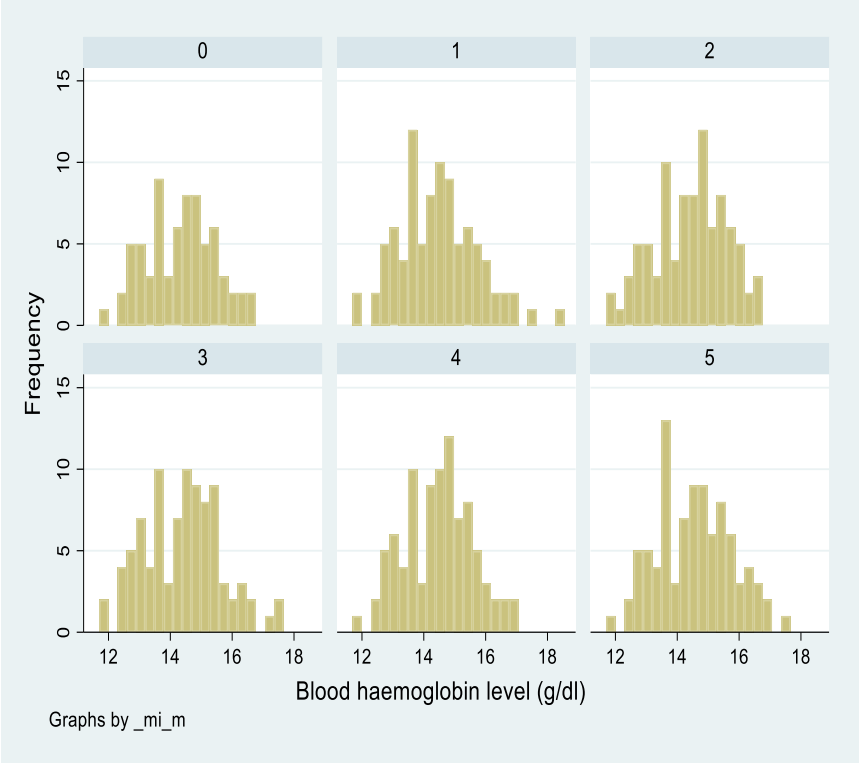

0
1
2
3
4
5
Frequency
Blood HDL level (mmol/l)
Graphs by _mi_m

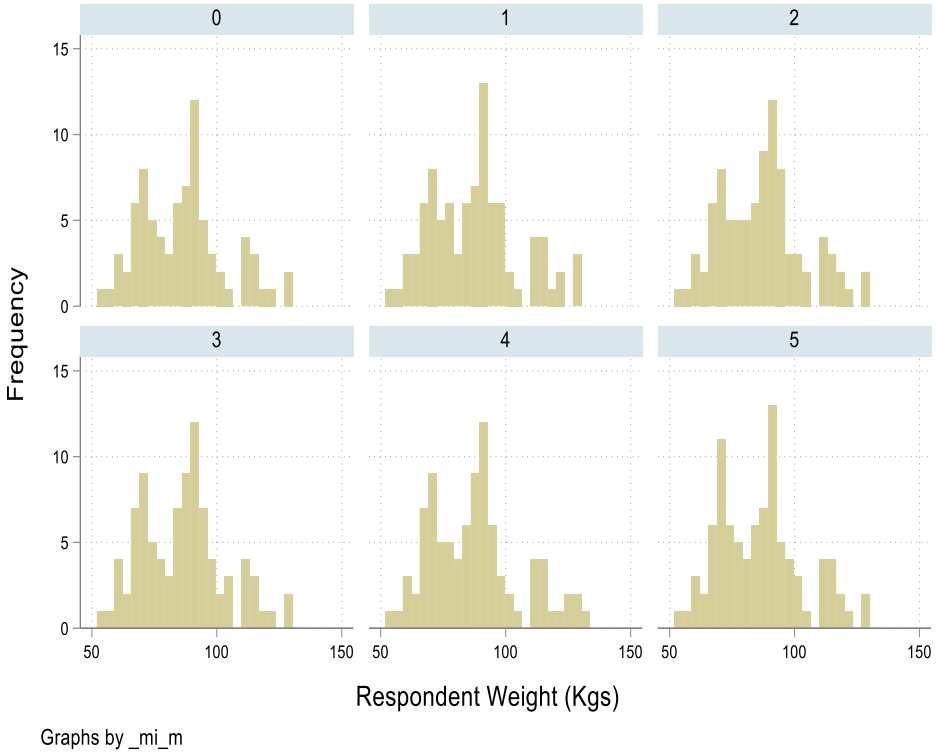



Graphs by _mi_m




Graphs by _mi_m


0
1
2
3
4
5
Frequency
0
5
10
15
12
14
16
18
Blood haemoglobin level (g/dl)
Graphs by _mi_m


0
1
2
3
4
5
Frequency
0
5
10
15
50
100
150
Respondent Weight (Kgs)
Graphs by _mi_m

## Appendix B2

### Descriptive characteristics for one representative imputed dataset (m = 1)

**M = 1**

| Group | Low TP(N=39) | High TP (N= 52) |
|---|---|---|
| Age (in years/ continuous) | | |
| Mean (SD) | 63.77 (5.67) | 64.08 (5.91) |
| Median (Q1, Q3) | 62.0 (59.0, 69.0) | 64.5 (60.0, 68.0) |
| Blood HDL level (mmol/l) | | |
| Mean (SD) | 1.39 (0.30) | 1.38 (0.35) |
| Median (Q1, Q3) | 1.3 (1.2, 1.5) | 1.3 (1.1, 1.6) |
| Blood LDL level (mmol/l) | | |
| Mean (SD) | 3.67 (1.48) | 3.34 (1.11) |
| Median (Q1, Q3) | 3.4 (2.6, 5.0) | 3.2 (2.3, 4.2) |
| Systolic blood pressure (mmHg) | | |
| Mean (SD) | 132.24 (16.23) | 131.05 (16.06) |
| Median (Q1, Q3) | 130.5 (120.4, 141.5) | 128.8 (119.8, 141.8) |
| Blood glycated haemoglobin level (%) | | |
| Mean (SD) | 6.34 (1.15) | 6.63 (1.29) |
| Median (Q1, Q3) | 5.9 (5.6, 6.8) | 6.2 (5.7, 7.2) |
| Weight (Kgs) | | |
| Mean (SD) | 87.01 (16.63) | 86.31 (17.80) |
| Median (Q1, Q3) | 86.5 (74.2, 95.2) | 86.0 (70.0, 96.6) |
| Heart rate (beats per minute) | | |
| Mean (SD) | 55.51 (11.67) | 55.71 (13.48) |
| Median (Q1, Q3) | 54.5 (48.7, 61.5) | 53.8 (46.8, 65.3) |
| White blood cell count (x10^9 cells/l) | | |
| Mean (SD) | 6.83 (2.19) | 6.65 (2.22) |
| Median (Q1, Q3) | 6.8 (5.3, 8.5) | 6.0 (5.0, 8.2) |
| Blood haemoglobin level (g/dl) | | |
| Mean (SD) | 14.58 (1.37) | 14.33 (1.17) |
| Median (Q1, Q3) | 14.4 (13.7, 15.6) | 14.4 (13.4, 15.1) |
| Gender (male/female) | | |
| female | 23 (59.0%) | 28 (53.8%) |
| male | 16 (41.0%) | 24 (46.2%) |
| Ethnicity (white/non-white) | | |
| white | 39 (100.0%) | 51 (98.1%) |
| non-white | 0 (0.0%) | 1 (1.9%) |
| Smoking (yes/no) | | |
| no | 33 (84.6%) | 43 (82.7%) |
| yes | 6 (15.4%) | 9 (17.3%) |

## Appendix C1 Regression outputs from the GEE and model RE for each behaviour in the form of Odds Ratios.

| **GEE models** | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | smoking | | alcohol | | physical | | fruit | | Sedentary | |
| Age | 0.939*** | [0.932,0.94] | 1.023*** | [1.016,1.03] | 0.947*** | [0.942,0.95] | 0.989*** | [0.983,0.99] | 1.054*** | [1.050,1.05] |
| Gender (female ref.) | | | | | | | | | | |
| Male | 0.807** | [0.705,0.92] | 1.423*** | [1.273,1.59] | 1.356*** | [1.242,1.48] | 0.979 | [0.873,1.09] | 0.631*** | [0.588,0.67] |
| Non pension wealth (1 ref.) | | | | | | | | | | |
| 2 | 0.469*** | [0.389,0.56] | 0.859 | [0.663,1.11] | 1.531*** | [1.272,1.84] | 0.836 | [0.681,1.02] | 0.621*** | [0.542,0.71] |
| 3 | 0.351*** | [0.287,0.428] | 0.911 | [0.709,1.172] | 2.197*** | [1.840,2.623] | 0.902 | [0.739,1.102] | 0.401*** | [0.351,0.458] |
| 4 | 0.202*** | [0.162,0.252] | 1.409** | [1.109,1.791] | 2.678*** | [2.251,3.187] | 0.806* | [0.661,0.983] | 0.322*** | [0.282,0.367] |
| 5 (highest) | 0.154*** | [0.123,0.193] | 1.982*** | [1.567,2.506] | 3.911*** | [3.308,4.625] | 0.957 | [0.790,1.159] | 0.219*** | [0.192,0.249] |
| Group (control ref.) | | | | | | | | | | |
| T2DM | 0.930 | [0.691,1.250] | 0.619** | [0.435,0.882] | 0.505*** | [0.369,0.691] | 1.149 | [0.831,1.588] | 1.913*** | [1.541,2.375] |
| Time | | | | | | | | | | |
| T1 | 0.862*** | [0.825,0.900] | 0.957 | [0.904,1.013] | 0.918** | [0.861,0.979] | 0.834** | [0.734,0.948] | 1.123*** | [1.070,1.179] |
| T2 | 0.695*** | [0.661,0.731] | 0.939* | [0.886,0.995] | 0.894*** | [0.841,0.950] | 0.943 | [0.841,1.058] | 1.291*** | [1.233,1.352] |
| Group#time interaction | | | | | | | | | | |
| T2DM#T1 | 0.757* | [0.607,0.943] | 1.037 | [0.773,1.390] | 1.036 | [0.689,1.558] | 1.382 | [0.865,2.208] | 0.833 | [0.647,1.073] |
| T2DM#T2 | 0.904 | [0.705,1.160] | 1.155 | [0.790,1.690] | 0.786 | [0.525,1.178] | 0.912 | [0.575,1.446] | 1.249 | [0.966,1.615] |
| *N* | 21483 | | 15582 | | 34879 | | 27679 | | 34879 | |
| *Groups* | 4,867 | | 3,705 | | 7,863 | | 6,443 | | 7.863 | |
| *Min* | 3 | | 3 | | 3 | | 3 | | 3 | |
| *Avg* | 4.4 | | 4.2 | | 4.4 | | 4.3 | | 4.4 | |
| *Max* | 5 | | 5 | | 5 | | 5 | | 5 | |

Exponentiated coefficients; 95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| **RE models** | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | smoking | | alcohol | | physical activity | | fruit | | Sedentary behaviour | |
| Age | 0.809*** | [0.787,0.832] | 1.055*** | [1.039,1.072] | 0.918*** | [0.911,0.926] | 0.987** | [0.980,0.995] | 1.095*** | [1.087,1.102] |
| Gender (female ref.) | | | | | | | | | | |
| Male | 0.556** | [0.367,0.844] | 2.298*** | [1.789,2.953] | 1.671*** | [1.464,1.907] | 0.987 | [0.864,1.128] | 0.458*** | [0.406,0.517] |
| Non pension wealth (1 ref.) | | | | | | | | | | |
| 2 | 0.0318*** | [0.0168,0.0602] | 0.744 | [0.429,1.291] | 1.902*** | [1.475,2.454] | 0.822 | [0.649,1.041] | 0.465*** | [0.376,0.576] |
| 3 | 0.0118*** | [0.00618,0.0227] | 0.826 | [0.486,1.403] | 3.219*** | [2.514,4.122] | 0.892 | [0.709,1.123] | 0.226*** | [0.183,0.279] |
| 4 | 0.00243*** | [0.00123,0.00480] | 2.374*** | [1.423,3.962] | 4.369*** | [3.430,5.565] | 0.783* | [0.623,0.984] | 0.155*** | [0.126,0.191] |
| 5 | 0.00143*** | [0.000716,0.00286] | 5.218*** | [3.158,8.622] | 7.891*** | [6.224,10.00] | 0.959 | [0.769,1.196] | 0.0804*** | [0.0653,0.0989] |
| Group (control ref.) | | | | | | | | | | |
| T2DM | 0.967 | [0.396,2.356] | 0.338** | [0.157,0.729] | 0.376*** | [0.246,0.574] | 1.164 | [0.776,1.745] | 2.856*** | [2.048,3.984] |
| Time (T0 ref.) | | | | | | | | | | |
| T1 | 0.467*** | [0.373,0.585] | 0.903 | [0.789,1.034] | 0.877** | [0.795,0.968] | 0.808** | [0.702,0.930] | 1.216*** | [1.121,1.319] |
| T2 | 0.145*** | [0.115,0.182] | 0.864* | [0.766,0.974] | 0.842*** | [0.774,0.917] | 0.931 | [0.827,1.049] | 1.535*** | [1.431,1.648] |
| Group#time interaction | | | | | | | | | | |
| T2DM#T1 | 0.291* | [0.109,0.774] | 1.095 | [0.509,2.353] | 1.060 | [0.619,1.815] | 1.470 | [0.834,2.592] | 0.742 | [0.510,1.082] |
| T2DM#T2 | 0.776 | [0.298,2.019] | 1.400 | [0.686,2.856] | 0.736 | [0.441,1.228] | 0.902 | [0.527,1.545] | 1.348 | [0.938,1.937] |
| | | | | | | | | | | |
| lnsig2u | 77.56*** | [71.26,84.41] | 11.34*** | [10.21,12.59] | 4.324*** | [3.975,4.703] | 2.021*** | [1.753,2.329] | 4.635*** | [4.322,4.970] |
| *N* | 21483 | | 15582 | | 34879 | | 27679 | | 34879 | |

Exponentiated coefficients; 95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$