The Economics of Type 2 Diabetes in Middle-Income Countries

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Abstract

This thesis researches the economics of type 2 diabetes in middle-income countries (MICs). Given the high prevalence of type 2 diabetes in MICs, in-depth country specific analysis is key for understanding the economic consequences of type 2 diabetes. The thesis consists of four studies with the unifying theme of improving the understanding of the causal impact of diabetes on economic outcomes. Study (1) provides an updated overview, critically assesses and identifies gaps in the current literature on the economic costs of type 2 diabetes using a systematic review approach; study (2) investigates the effects of self-reported diabetes on employment probabilities in Mexico, using cross-sectional data and making use of a commonly used instrumental variable approach; study (3) revisits and extends these results via the use of a fixed effects panel data analysis, also considering a broader range of outcomes, including wages and working hours. Further, it makes use of cross-sectional biomarker data that allow for the investigation of undiagnosed diabetes. Study (4) researches the effect of a diabetes diagnosis on employment as well as behavioural risk factors in China, using longitudinal data and applying an alternative identification strategy, marginal structural models estimation, while comparing these results with fixed effects estimation results. The thesis identifies a considerable economic burden of diabetes in middle-income countries and uncovers several inequities affecting women, the poor and the uninsured. Biomarker results indicate that the adverse effects are limited to those aware of their diabetes. Finally, women are also found to achieve fewer positive changes of their behavioural risk factors after a diabetes diagnosis than men, offering a potential explanation for their more adverse employment outcomes compared to men. To reduce the economic burden, the groups most affected by the identified inequities should be targeted. Further, the underlying reasons for the found sex differences need to be identified.

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Publications and statement of authorship

The research reported is my own original work which was carried out in collaboration with others as follows:

Chapter 1: Written by Till Seuring.

Chapter 2: Till Seuring was the lead author of a paper published as:

Seuring, T., Archangelidi, O., and Suhrcke, M. (2015a). "The Economic Costs of Type 2 Diabetes: A Global Systematic Review." *PharmacoEconomics* 33 (8), 811–831.

Till Seuring, Marc Suhrcke and Olga Archangelidi designed the study. The search strategy was designed and executed by Till Seuring. Till Seuring and Olga Archangelidi screened the initial results and extracted the data from the primary studies. Till Seuring drafted the original manuscript which was critically reviewed by Olga Archangelidi and Marc Suhrcke.

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[1] See also Schmittdiel (2016).

Abbreviations

BMI body mass index

CHNS China Health and Nutrition Survey

CHARLS China Health and Retirement Longitudinal Study

COI cost-of-illness

DAG direct acyclic graph

FE fixed effects

GDP gross-domestic-product

HbA1c glycated hemoglobin

HIC high-income country

ICD International Statistical Classification of Diseases and Related Health Problems

IDF International Diabetes Federation

IV instrumental variable

IPTW inverse probability of treatment weights

LIC low-income country

LMIC low- and middle-income country

LPM linear probability model

MSM marginal structural model

MIC middle-income country

MxFLS Mexican Family Life Survey

NCD non-communicable disease

OLS ordinary least squares

OOP out-of-pocket

PPP purchasing-power-parity

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses

RE random effects

UK United Kingdom

WHO World Health Organization

WTP willingness to pay

1 General introduction

Background to the thesis

Diabetes, and especially type 2 diabetes, has seen an unprecedented rise in prevalence globally and especially in low- and middle-income countries (LMICs), where rates reached and often surpassed those of high-income countries (HICs), such as the USA, UK or Germany (Hu, 2011; NCD Risk Factor Collaboration, 2016). Today, two-thirds of the over 400 million people with diabetes live in LMICs (International Diabetes Federation, 2014) and, in particular, in China, India, Brazil, Indonesia, Pakistan, Russia, Egypt and Mexico (NCD Risk Factor Collaboration, 2016). In 2015, diabetes has been responsible for over 5 million deaths and people with diabetes are estimated to die 6 years earlier due to the disease and increasingly before the age of 60 (International Diabetes Federation, 2015; Seshasai et al., 2011). This increase in prevalence is due to a shift in age structure towards older populations and is further spurred by rapid changes in levels of physical activity, nutrition and other lifestyle related factors (Hu, 2011; NCD Risk Factor Collaboration, 2016).

In LMICs, the rise of non-communicable diseases (NCDs) has in many cases led to a double disease burden, where health systems have to deal with high rates of infectious as well as non-communicable diseases (Jamison et al., 2013). Given the scarce resources in these countries (Mills, 2014), the increasing number of people with diabetes and at risk of the disease are putting an additional burden on these systems (Chan et al., 2016; Wareham et al., 2016). However, despite the epidemic levels diabetes has reached in LMICs, research on its economic consequences has remained sparse for these countries and mostly limited to HICs. More research is needed to identify how diabetes is affecting individuals in LMICs, and the groups most adversely affected. This could help raise awareness of policy makers of the size and of the potential inequities of the disease burden, and help to design strategies to reduce these inequities.

Currently healthcare systems in LMICs are likely further increasing inequities by providing better care and coverage for those in formal employment and economically better off (Di Cesare et al., 2013; Mills, 2014). For Peru, a recent study identified several barriers to care for people with diabetes, that are likely highly relevant for other middle-income countries (MICs) as well. They included a generally low political commitment to improve access to and the quality of diabetes care, little qualified personnel to treat diabetes at the primary care level, high out-of-pocket expenditures, partly related to the seeking of specialized diabetes care in the private sector, and few resources in the healthcare budget being allocated to non-communicable-diseases treatment despite its high mortality burden (Cardenas et al., 2016). Further, it appears that a diabetes diagnosis often happens too late to prevent first complications, with a first diagnosis frequently

being made after a patient has been admitted to a hospital emergency department due to diabetes related complications (Cardenas et al., 2016). Similar observations have been made for other LMICs (Beran, 2015; World Health Organization, 2014).

Types of diabetes

Diabetes is a term used to describe various conditions characterised by elevated blood glucose levels. These either occur because the pancreas is not able to produce sufficient insulin, or due to insulin resistance, where the body is not able to use the produced insulin effectively (World Health Organization, 2016). The different conditions themselves have distinct origins, especially the two most common types called type 1 diabetes and type 2 diabetes.

- **Type 1 diabetes** is an autoimmune disease with an important genetic component and whose triggers still remain largely elusive. It emerges when the insulin producing cells on the pancreas are attacked and destroyed by the immune system and insulin has to be provided exogenously. About 10% of all global diabetes cases are type 1 diabetes and it is particularly prevalent in Northern European countries, such as Finland, though it generally exhibits much geographic variation. Its onset is mainly during the first 30 years of life. Symptoms tend to appear rather quickly and can be quite severe, leading to a relatively rapid diagnosis or death if insulin is not given or available. People with type 1 diabetes will need to inject insulin to control their blood glucose levels for their entire life following diagnosis (Tuomilehto, 2013).

- **Type 2 diabetes** results from the body's ineffective use of insulin and accounts for about 90% of all diabetes cases (World Health Organization, 2016). Albeit there is a considerable genetic component to the development of type 2 diabetes, there are many known risk factors that favour the development of type 2 diabetes, such as overweight and obesity, an unhealthy diet, physical inactivity and smoking, among others (American Diabetes Association, 2014; World Health Organization, 2016). Interestingly, the risk to develop type 2 diabetes varies also by ethnicity, with South-East Asian populations developing diabetes at lower body mass index (BMI) levels than populations of European decent (Ramachandran et al., 2010). Type 2 diabetes often remains undetected for several years due to its more gradual development compared with type 1 diabetes (American Diabetes Association, 2014). Therefore, even in HICs and especially in LMICs, a proportion of at least 1/4 of the population with type 2 diabetes is unaware

of the condition (Beagley et al., 2014).

The onset of type 2 diabetes also appears to be increasingly earlier in life. This has been observed mainly in ethnic minorities in HIC, such as Mexicans and Asians, while data are limited for LMICs (Fazeli Farsani et al., 2013). Also, the increasing numbers of obesity in child- and early adulthood are leading to the earlier onset of type 2 diabetes (Chen et al., 2011). Hence, type 2 diabetes increasingly affects people in the middle of their productive lifespan, extending the time they have to live with the disease and the probability of developing debilitating complications.

Diabetes complications

The most common complication for all types of diabetes, and often already present at diagnosis, is retinopathy (35% at diagnosis), being responsible for 2.6% of blindness globally. Further, up to 50% of cases of end stage renal disease are a direct result of diabetes, especially in countries where access to dialysis is restricted. People with diabetes also have a 2–3 times higher risk to experience cardiovascular disease compared to people without diabetes. A further complication is amputation of lower limps due to impaired wound healing, being 10–20 higher for people with diabetes. In addition to these microvascular complications, diabetes has its greatest health impact as a risk factor for cardiovascular disease and stroke (World Health Organization, 2016). There is also a growing literature suggesting a—potentially bidirectional—relationship between diabetes and depression (Dooren et al., 2013; Nouwen et al., 2010; Roy et al., 2012). In addition, there seems to be a link between diabetes and the development of certain types of cancer, (Nead et al., 2015; Tsilidis et al., 2015), as well as an array of other infectious diseases, intentional self-harm and degenerative disorders diseases (Seshasai et al., 2011).

Diabetes prevention

Diabetes complications are a result of consistently elevated blood glucose levels, and are aggravated if blood pressure is high as well, as is often the case. Hence many complications could be prevented if recommended treatment goals were achieved. However, limited resources and access to healthcare make it difficult to properly treat type 2 diabetes in LMICs (Villalpando et al., 2010), and even in HICs a large part of the population with diabetes does not achieve treatment goals to prevent complications (Diabetes UK, 2012).

Primary prevention of diabetes or at least a delayed onset are further major goals of diabetes research and could be achieved by reducing the prevalence of the

known risk factors such as obesity, an unhealthy diet and sedentary behaviour (World Health Organization, 2016). However, so far most approaches to prevent type 2 diabetes have not had the desired effect and may not always be realistic in very resource constrained settings (White, 2016). In particular efforts to reduce the biggest type 2 diabetes risk factors of obesity and overweight have been unsuccessful (Roberto et al., 2015).

The need for further economic research on diabetes

To design effective interventions and to make qualified decisions about the use of primary and secondary prevention strategies of diabetes, researchers and policy makers need information about the current burden of diabetes, both in terms of health and economically. Information on all aspects of economic costs and, optimally, the quality of the estimates has to be available. In particular, in LMICs equity issues are likely to be of importance if the burden of diabetes varies by socioeconomic groups, ethnicity or sex, potentially widening existing socioeconomic inequities. However, at the start of this thesis, little was known about the economic impact of diabetes in developing countries. There had, to my knowledge, not been a comprehensive systematic review of studies assessing the costs related to diabetes, both in terms of direct and indirect costs. One (non-systematic) review existed (Ettaro et al., 2004), including cost-of-illness (COI) studies published until the year 2001. Completely absent in that review were studies from LMICs. Further, considerable time had passed since that review and the methodological quality of research published since then needed to be assessed and areas of future research had to be identified. Also missing was a comprehensive overview of studies using quantitative methods to estimate the impact of diabetes on labour market outcomes, such as employment and wages.

Objectives of the thesis

The thesis focuses on three main research questions related to the economics of diabetes in MICs.

1. What is the worldwide evidence on the economic burden of type 2 diabetes, both in terms of COI and the labour market effects of diabetes?
2. What is the impact of diabetes on labour market outcomes in MICs?
3. How does a diabetes diagnosis affect behavioural risk factors?

These three research questions are answered in Chapters 2, 3, 4 and 5 and several sub-themes are explored. These include potential inequities of the economic burden of diabetes, time trends in the impact of diabetes on labour market

outcomes and behavioural risk factors, heterogeneities in the impact of diabetes between those aware and those unaware of the condition, and the robustness of the estimates to different estimation techniques and geographic settings.

The economic burden of diabetes across the globe

Chapter 2: *The Economic Costs of Type 2 Diabetes: A Global Systematic Review* provides a first comprehensive global picture of the economic burden of type 2 diabetes, including both COI studies and studies on the labour market effects of diabetes from both HICs and LMICs. The aim was to provide information on the economic costs of diabetes for as many countries as possible. Another goal was the identification of research areas, both in terms of methodology and topic, where evidence was lacking and/or current methodologies could be improved upon. This was intended to guide the subsequent chapters of this thesis as well as other researchers interested in the economics of diabetes. Chapter 2 thereby answers research question one.

The labour market impact of type 2 diabetes

The review identified the labour market impact of diabetes in LMICs as a topic that had not received much attention. Apart from the lack of evidence from developing countries, there was also scope for methodological improvements compared to the existing HIC evidence. Further, information on the effects on subpopulations, i.e. comparisons between rich and poor and the formal and informal labour market were non-existent.

However, in order to carry out such an analysis, appropriate data needed to be identified. To this end, a search for suitable household data from LMICs was carried out, using general as well as specialized search engines, such as the World Bank Central Microdata Catalog `http://microdata.worldbank.org/`, the Demographic and Health Survey Database `http://dhsprogram.com/data/`, the Global Health Data Exchange Database `http://ghdx.healthdata.org/`, and the International Household Survey Network Catalog `http://catalog.ihsn.org/index.php/catalog`. The aim was to identify datasets containing information on self-reported or measured diabetes. Specialized websites providing an overview on household survey data in developing countries were also scoped to identify relevant data (such as `http://ipl.econ.duke.edu/dthomas/dev_data/index.html` and `https://sites.google.com/site/medevecon/development-economics/devecondata/micro` for household survey from developing countries, and an overview on datasets containing biomarker information provided by The Biomarker Network at `http://gero.usc.edu/CBPH/network/resources/studies/`). An overview of the identified surveys is provided in Table A1 in the appendix.

Given the availability of data and the extent of diabetes in MICs compared to low-income countries (LICs), a decision was made to focus on MICs for the remainder of the thesis and, in particular, on Mexico and China. The main reason was the availability of suitable data provided by the Mexican Family Life Survey (MxFLS) and China Health and Nutrition Survey (CHNS). First, the MxFLS was used to investigate the impact of diabetes on labour market outcomes in Mexico, as the data provided information on important covariates, including parental diabetes, not available in other surveys. Further, Mexico is a country with particularly high obesity and diabetes rates making it an interesting case to study. Chapter 3 therefore investigates the causal effect of diabetes on employment probabilities in Mexico, providing answers to research question two.

Identification of the causal effect of diabetes on labour market outcomes

As is eluded to in Chapter 3, identifying a causal relationship of diabetes with labour market outcomes is being complicated by the possibility of unobserved time-variant and -invariant heterogeneity. In Chapter 3, an instrumental variable (IV) approach was used, as a first step of analysis, to address this research question. However, as is often the case with IVs, the identification strategy is imperfect and it remains open to debate whether the used instrument fully satisfies the exclusion restriction, even if formal econometric testing suggests it does, leaving the possibility of biased estimates. Several other strategies potentially exist to identify the true effect of diabetes on labour market outcomes using quasi-experimental econometric approaches (Antonakis et al., 2012). For example, a natural experiment—that would affect people's diabetes risk while at the same time have no direct effect on labour market outcomes such as employment probabilities or wages—may be used. However, a setting with exogenously introduced variation is notoriously difficult to find (moreover, it may provide information only for a very—often geographically or economically—specific population that has been exposed to this natural experiment). Another strategy to improve inference is the use of panel data and in particular the fixed effects (FE) estimation, which does not depend on exogenously introduced variation. Relying only on within-individual variation, the strategy allows to fully account for time-invariant factors that may affect diabetes and labour market outcomes simultaneously. This is likely of importance in the case of diabetes and economic outcomes, where the use of IVs has been motivated by the possibility that unobserved character trades—generally thought to be stable over time—,such as motivation as well as early life experiences, may be confounding the relationships (Seuring et al., 2015b).

Therefore, part one of Chapter 4 takes advantage of a recent addition of data to

the MxFLS to apply a FE estimation approach, testing if the effects of diabetes on employment probabilities found in Chapter 3 are robust to using this alternative identification strategy. Further, it extends the number of investigated outcomes to three, adding wages and working hours.

Do the effects of diabetes change over time?

Diabetes is a lifelong disease whose debilitating complications generally appear after several years of elevated blood glucose levels (World Health Organization, 2016). So far, little is known about the exact time after diagnosis that diabetes starts exhibiting potential adverse effects on labour market outcomes. However, in order to design strategies to mitigate the economic impact of diabetes this would be important to know as it would help in finding the most efficient point in time to intervene. If effects occur immediately after diagnosis, it may be because severe complications are already present at the point of diagnosis, leaving little possibilities to prevent the economic burden. This would suggest that much could be prevented by an earlier diagnosis and appropriate treatment and lifestyle changes. It could further indicate a potential effect of the diagnosis itself, for example on psychological health, causing reductions in employment probabilities or wages. However, if effects appear only years after the diagnosis, severe diabetes complications that have developed due to sub-optimal blood glucose management may be causing the reductions in productivity. This could hint at a possibility to mitigate the negative economic consequences of diabetes by secondary prevention through better diabetes management even without an earlier diagnosis. The systematic review in Chapter 2 showed a lack of evidence in this area. Only one study by Minor (2013) investigated the long term consequences of diabetes, finding non-linear effects in a USA population. Apart from the need for additional evidence, also several possibilities for methodological improvements exist. Part two of Chapter 4 therefore assesses the impact of the time since diagnosis on labour market outcomes, using both linear and non-linear specifications in a FE framework.

Measurement of diabetes in household surveys

There are two possibilities of measuring diabetes in household surveys: (1) asking participants about their diabetes status or (2) identifying people with diabetes using biometric tests, such as fasting blood glucose or glycated hemoglobin (HbA1c) levels. Using self-reported information likely leads to the exclusion of a considerable part of the population with diabetes that has not yet received a diagnosis by a healthcare professional (Beagley et al., 2014). Using biomarker information, also previously undiagnosed cases can be identified. Blood glucose measurements

provide information on glucose levels at the time of the blood draw but it is not possible to infer on glucose levels over time. They are also sensitive to food consumption and may lead to false positives if taken in a non-fasted state. HbA1c levels provide an indication of the average blood glucose levels over the preceding three months and are not sensitive to the glucose level at the time of the blood draw (World Health Organization, 2011). They are, however, sensitive to an array of disorders such as haemoglobinopathies, anaemias, and disorders associated with accelerated red cell turnover (World Health Organization, 2011). The cut-off points for diabetes detection for blood glucose measurement and HbA1c measurement are 126 mg/dl and 6.5%, respectively (World Health Organization, 2006, 2011).

Unfortunately, and largely due to data limitations, previous research had to rely mainly on self-reported diabetes information. It has therefore remained unclear if the effects found also extended to the population with diabetes unaware of its condition. Part 3 of Chapter 4 uses a relatively large sample of biomarker data with HbA1c measurements, made available in wave 3 of the MxFLS that was released in 2015, to investigate the extent of the undiagnosed population in Mexico and the association of diabetes with labour market outcomes for the entire and undiagnosed population with diabetes. This part also addresses the question if current disease severity, as proxied by HbA1c levels, is related to labour market outcomes.

Overall, the three parts of Chapter 4 provide extensive additional evidence to answer research question two, by providing evidence of the effect of diabetes on employment probabilities using an alternative estimation strategy compared to Chapter 3, extending the investigated outcomes to wages and working hours and providing evidence on the effects of diabetes duration. Finally, it investigates heterogeneities in the effects of diabetes for the entire population with diabetes, i.e. those aware as well as those unaware of their condition.

Diabetes, behavioural risk factors and employment status

Previous research on the impact of diabetes on employment has assumed a non-dynamic relationship between diabetes and employment probabilities, with diabetes affecting employment but employment not affecting diabetes. This, however, may be a too restrictive assumption, for example if employment status affects behavioural risk factors such as smoking, alcohol consumption or weight that can affect the likelihood of developing diabetes. However, simply accounting for these risk behaviours in a non-dynamic framework may also lead to biased estimates as it is likely that these risk factors themselves are affected by a diabetes diagnosis as people try to live healthier to prevent further diabetes complications

or through the effects of medications. This also makes it impossible to account for the potential effect of obesity on labour market outcomes when trying to identify the causal effect of diabetes in such a framework.

These behavioural risk factors also themselves represent an important outcome to investigate, given that there is evidence that the adverse impact of diabetes could be at least partly prevented by changes in lifestyle and appropriate treatment (Wareham et al., 2016). This would require a diagnosis of diabetes, in order to create awareness of the disease. As Chapter 4 has shown for Mexico, a large part of the population with diabetes is unaware of its condition, whether in HICs or developing countries (Beagley et al., 2014). But even once a diagnosis has been made, appropriate changes towards a healthier lifestyle and medical treatment are required to prevent complications and are only possible if the type of information about ways to achieve this is accessible to and understood by the person with diabetes. This information is typically provided by a healthcare professional at the time of diagnosis and thereafter. Relatively little is known about the extent to which people with diabetes are making such changes after a diagnosis, especially in MICs, where healthcare access and health literacy is likely more limited than in HICs (Mills, 2014).

Research study three in Chapter 5 investigates the effect of a diabetes diagnosis on both employment probabilities and health behaviours in China, using six waves of very detailed panel data from the CHNS. China, like Mexico, is a country where diabetes rates have increased dramatically over the last decades, now affecting about 100 million people or close to 10% of the adult population (NCD Risk Factor Collaboration, 2016), with many remaining unaware of having the condition (Wang et al., 2015). In a first step to take into account the potential interrelatedness of diabetes, employment status and behavioural risk factors, the study uses marginal structural models (MSMs), which are able to account for time-variant confounding. This strategy allows adjusting for the fact that behavioural risk factors and also employment status could be causes as well as effects of diabetes, which cannot be distinguished with traditional econometric methods, such as ordinary least squares (OLS) or FE. To further investigate the potential sources of bias and robustness of the results also a FE and random effects (RE) approach are used. This chapter intends to answer research question three by providing evidence on the effect of a diabetes diagnosis on behavioural risk factors and by taking into account the potential relationship with employment as well. It thereby also provides further evidence to answer research question two, using a different estimation strategy and information from a different country, and also suggests that future research should try to model employment and health behaviours simultaneously to uncover the underlying pathways through which they may affect each other.

Thesis methods and structure

This research uses systematic review and advanced quantitative methods to answer the research questions that together form this thesis.

A series of four independent research studies form this thesis. Chapters 2 and 3 have already been published as journal articles and Chapter 4 has been published as a discussion paper and has been submitted to an international peer reviewed journal the time of completion of the thesis. Chapter 5 will be submitted within the next months. This is outlined in more detail in the publication and statement of ownership section. Each study addresses different research questions, but has the investigation of the labour market impact of diabetes as a unifying theme. Taken together the studies progressively complement each other, providing a better understanding of the economic impact of diabetes in MICs. Each study is presented in a separate chapter. For Chapters 3, 4 and 5, a pre-amble precedes the actual study to contextualize the respective findings with the preceding chapter and the entire thesis.

2 The economic costs of type 2 diabetes: a global systematic review

Abstract

There has been a widely documented and recognized increase in diabetes prevalence not only in high-income countries (HICs) but also in low- and middle-income countries (LMICs), over recent decades. It is less clear what is the economic burden associated with diabetes, especially in LMICs. We provide a systematic review of the global evidence on the costs of type II diabetes. Our review seeks to update and considerably expand the previous major review of the costs of diabetes by capturing the evidence on overall, direct and indirect costs of type II diabetes worldwide that was published since 2001. In addition we include a body of economic evidence that has hitherto been distinct from the cost-of-illness (COI) work, i.e. studies on the labour market impact of diabetes. PubMed, EMBASE, EconLit and IBSS were searched (without language restrictions) for studies assessing the economic burden of type 2 diabetes published from January 2001 to October 2014. Costs reported in the included studies were converted to international dollars ($) adjusted for 2011 values. Alongside the narrative synthesis and methodological review of the studies we conduct an exploratory linear regression analysis, examining the factors behind the considerable heterogeneity in existing cost estimates between and within countries. We identified 86 COI and 22 labour market studies. COI studies varied considerably in both methods and cost estimates, with most studies not using a control group, though the use of either regression analysis or matching has increased. Direct costs were generally found to be higher than indirect costs. Direct costs ranged from $242 for a study on out-of-pocket (OOP) expenditures in Mexico to $11917 for a study on the cost of diabetes in the USA, while indirect costs ranged from $45 for Pakistan to $16914 for the Bahamas. In LMICs—in much contrast to HICs—substantial part of the cost burden arose to patients from OOP treatment costs. Our regression analysis revealed that direct diabetes costs are closely and positive associated with a country's gross domestic product (GDP) per capita, and that the USA stood out as having particularly high costs, even after controlling for GDP per capita. Studies on the labour market impact of diabetes were almost exclusively confined to HICs and found strong adverse effects, particularly for male employment probabilities. Many of these studies also took into account the possible endogeneity of diabetes, which was not the case for COI studies. The reviewed studies indicate a large economic burden of diabetes, most directly affecting patients in LMICs. The magnitude of the cost estimates differs considerably between and within countries, calling for the contextualization of the study results. There remains large scope for adding to the evidence base on labour market effects of diabetes in LMICs. Further, there is a need for future COI studies to incorporate more advanced statistical methods in their analysis to account for possible

biases in the estimated costs.

Introduction

Diabetes is a chronic disease that has spread widely, not only in high-income but also in many LMICs over the last decades. The most recent data from the International Diabetes Federation indicate that diabetes affected 382 million people worldwide in 2013, a number that is expected to grow to 592 million by 2035. The estimated global prevalence in 2013 amounts to 8.3% among people aged 20–79 years, with the world's most populous countries India and China reaching prevalence rates between 9% and 10%, corresponding to 65 and 100 million in absolute numbers, respectively. Particularly high prevalence rates are found in Mexico (12.6%) and Egypt (16.8%), surpassing the rates of most HICs, including the USA (9.2%) and Germany (8.2%) (International Diabetes Federation, 2014). Taken together, in 2013 about two-thirds of all individuals with diabetes lived in LMICs (International Diabetes Federation, 2014). The rising prevalence of diabetes in LMICs appears to be fuelled by rapid urbanization, nutrition transition and increasingly sedentary lifestyles (Hu, 2011). The most prevalent form of diabetes by far is type 2 diabetes, affecting about 90% of people with diabetes while the remaining 10% mainly have type 1 diabetes or gestational diabetes (International Diabetes Federation, 2014).

Due to its adverse effect on people's health, diabetes also imposes an economic burden on individuals and households affected as well as on healthcare systems. The economic burden of diabetes was confirmed by a review of COI studies on diabetes mellitus, published in 2004, covering the literature up to the year 2000. The authors concluded that the direct and indirect economic burden of diabetes was "large", and that costs had increased over time. However, the review also noted that significant variation in costing methodologies made it near impossible to directly compare the cost estimates. However, the studies reviewed by Ettaro et al. (2004) were almost exclusively focused on the USA, with a small part coming from European HICs and none from LMICs. The aim of this study is therefore to systematically review the literature on the economic costs of diabetes published since 2001 (i.e. the first year not covered by the Ettaro et al. (2004) review), as we expect a considerable number of new studies also from LMICs. In addition to the COI studies we review the literature on labour market outcomes, with a specific interest in the methodological challenges involved. In doing so we substantively update and expand the scope of the Ettaro et al. (2004) review, allowing us to revisit its findings regarding the evidence base about the economic burden of type 2 diabetes globally.

COI studies generally assess the direct and indirect costs of a particular illness,

where the former represent the opportunity cost of resources used for treatment. The indirect costs measure the value of resources lost due the illness, most commonly those caused by losses in productivity due to mortality and morbidity as measured in lost earnings (Segel, 2006). In addition, another approach also focuses on estimating the impact of diabetes on labour market outcomes. However, rather than trying to estimate the monetary losses that arise from a decrease in productivity, these studies typically compare labour market outcomes (e.g. employment probabilities, earnings or lost work days) between people with and without diabetes, while accounting for differences in age, education and other demographic and socioeconomic variables, that might arise between both groups and that could affect labour market outcomes as well as the chances of developing diabetes. The aim of studies in this field is to obtain a clearer picture of how diabetes causally affects these labour market outcomes, without necessarily monetizing the results. Because of the different methodologies and data requirements, these studies tend to differ considerably from traditional COI studies, which is why we reviewed them separately. To the best of our knowledge this is the first review that systematically assesses the studies in this particular field.

Methods

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were used as a basis for the overall study approach (Moher et al., 2009).

Search strategy

The electronic search was based on the following search terms: "Diabetes Mellitus"[Mesh] AND ("Costs and Cost Analysis"[Mesh] OR "Cost of Illness"[Mesh] OR "Employment"[Mesh] OR "labour Market"[All fields] OR "Labour Market"[All fields] OR "Productivity"OR "Willingness to pay"[All fields]). The above search was run in PubMed and was then adapted for searches in EMBASE, EconLit and the International Bibliography of the Social Sciences (IBSS). The search was carried out from October 2012 to October 2014 and restricted to studies published between January 2001 and October 2014, as the earlier review had covered COI studies until 2000 (Ettaro et al., 2004). No language restrictions were applied. The references were downloaded in RIS format where possible and then transferred to Mendeley. Authors were contacted for further information if clarification was needed after the full text analysis.

Inclusion and exclusion criteria

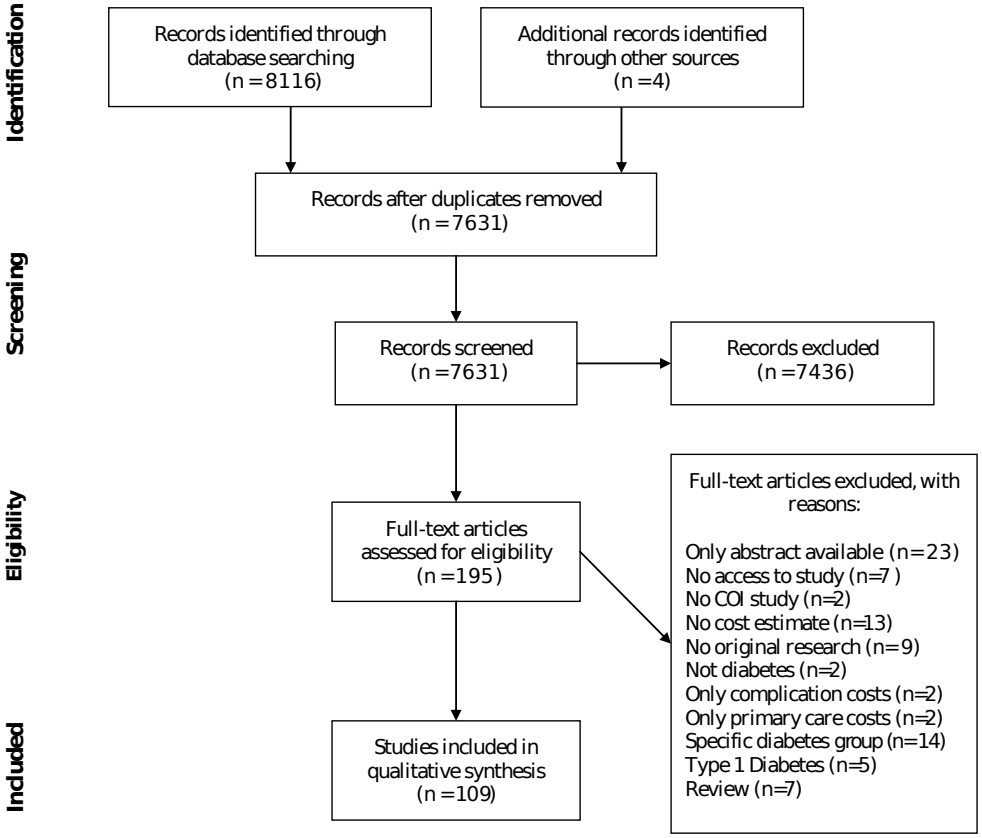
Studies were eligible if a monetary estimate of the direct and/or indirect costs of diabetes was presented in the results section or if studies provided an estimate of the impact of diabetes on labour market outcomes (employment probabilities, labour income, wages and lost work days). We did not exclude studies with a small sample size as this might have discriminated against studies in LMICs. Studies on types of diabetes explicitly different from type 2 diabetes were excluded. However, we included studies that did not explicitly mention the type of diabetes, given that type 2 diabetes accounts for about 90% of all diabetes cases. Studies exclusively assessing the costs of diabetes complications or the costs of management strategies were excluded as were studies estimating the costs for specific groups with diabetes (e.g. costs for people with poorly controlled diabetes), since we were interested in the costs incurred to populations comprising the whole spectrum of people with type 2 diabetes. Editorials, reviews and studies for which the full text could not be retrieved or only an abstract was available were also excluded.

Data extraction and analysis

Data extraction was carried out by two investigators (TS and OA). After duplicates were removed, titles and abstracts were scanned by one researcher (TS) to identify studies suitable for a full text review. The process was checked by a second researcher (OA) on a random subsample of 2000 studies of the retrieved references. The full text was subsequently retrieved for the identified studies and they were reviewed by two researchers (TS and OA), with disagreements resolved by discussion. Finally, 109 studies were identified (see Figure 1) that fulfilled the inclusion criteria and data extraction was carried out using a pre-defined extraction table. Primary outcomes were the total costs, the direct costs, and the indirect costs of type 2 diabetes and the respective per capita estimates of these outcomes, as well as the impact of type 2 diabetes on employment probabilities, income, wages and lost work days. Secondary outcomes comprised the methodology used to assess the monetary costs of type 2 diabetes, the range of cost factors included in the analysis, as well as the methodology used to assess the labour market impact of diabetes. Further extracted information included the year of publication, year of data collection, the time horizon, the country or region studied, the data source, sample size and age as well as information on whether the study distinguished between types of diabetes.

We present the COI study results in per capita values to facilitate comparability across countries. For studies presenting overall population level estimates rather than per capita costs information, we calculated those costs, whenever possible,

Figure 1: PRISMA flowchart.



using the diabetes prevalence mentioned in the respective study. If no total cost estimate was presented but information on direct and indirect costs was available, then direct and indirect costs were added up to produce a total cost estimate. We converted costs into purchasing-power-parity (PPP) adjusted US$ estimates, also referred to as international dollars and henceforth denoted with the $ sign, in order to further increase comparability. Since some studies did not present the data in the country's local currency but in US$ or some other major currency, we used the exchange rate given in the article to convert the estimates back into the local currency. If no exchange rate was provided in the study itself, we used the average exchange rate[1] for the reported year. The PPP adjusted estimates for the year 2011 were then calculated using the Campbell and Cochrane Economics Methods Group Evidence for Policy and Practice Information and Coordination Centre (CCEMG-EEPPI Centre) cost converter (Shemilt et al., 2010). For all additional analyses carried out in the following sections only studies for which a mean cost estimate was presented or could be calculated, were included. Further, in the case of a study presenting estimates for more than 1 year, only the estimate for the most recent year was used for the analysis. For studies presenting both incremental and total cost estimates, only the incremental cost estimate was taken into account.

Studies were further classified into two groups according to the level of economic development of the investigated country—(1) high-income and (2) LMICs (LMICs)—according to the historical World Bank income group classification of the respective country in the year that data collection for the respective study had taken place (World Bank, n.d.). Where necessary due to space constraints we used abbreviations for country names, as detailed in Table A2 in the appendix.

In order to explore the factors involved in the variation of direct costs reported in COI studies, we first plotted the direct per capita costs in relation to the gross-domestic-product (GDP) per capita of the respective country and provided an estimate of the relationship using linear regression. We then conducted an exploratory regression analysis, with the annual direct cost per patient as the dependent variable to investigate what other factors might explain the variation in direct cost estimates. The set of independent variables comprised (1) the estimation approach in each study, (2) the year of data used, (3) GDP per capita of the studied country in international dollars, (4) an indicator of whether the study was conducted in the USA, (5) an indicator of whether the study was deemed to be nationally representative, and (6) a variable indicating whether the study had explicitly taken diabetes-related complications into account. The year of the data used was considered because the development of social security systems and treat-

[1]Midpoint exchange rate according to OANDA historical exchange rates—[`http://www.oanda.com/currency/historical-rates/`]

ment methods may affect how the direct costs evolve over time. We categorized this variable into groups: studies using data from before 1995, 1995 to 1999, 2000 to 2004, 2005–2009 and 2010–2004. The dummy variable for studies on the USA was included to account for the generally higher healthcare expenditures in the USA compared with other HICs with similar per capita income levels (Laugesen et al., 2011). Accounting for national representativeness should control for any effects that might be driven by those studies that estimate costs for sub-national, regional- or city-level population samples. Including an estimator for diabetes complications should account for the possible underestimation of diabetes costs in studies excluding complications. We exclude country estimates extracted from multi-country studies in our preferred specification, as their inclusion would lead to an over-statement of the cost effect of the estimation method employed in the given multi-country study.

Results

Due to the differences in methodologies, we first present the findings on the identified COI studies and subsequently turn to studies on labour market outcomes.

Cost-of-illness studies on type 2 diabetes

Number of studies

We identified a total of 86 relevant COI studies (see Table A3 in the appendix for a detailed description of the included studies), of which 62 focused on HICs, 23 on LMICs, and one multi-country study covered both HICs and LMICs. Studies in LMICs increased over time, with the majority of the LMIC studies being published between 2007 and 2014. Six of the selected studies were multi-country studies, of which two (Kirigia et al., 2009; Smith-Spangler et al., 2012) did not provide detailed cost estimates for every country in the study and one did not provide a year for the estimated costs, so that we could not calculate estimates in international dollars (Boutayeb et al., 2014). Therefore, we could not include these particular studies in our country-specific analysis.

Regional distribution

In terms of geographic regions, most studies were carried out on countries in Latin America and the Caribbean (n=38) and Europe (n=37), followed by the USA and Canada (n=26), East Asia and Pacific (n=11), the Middle East and North Africa (n=5), South Asia (n=4), Sub-Saharan Africa (n=4) and Australia (n=1). The number of countries studied is higher than the number of articles reviewed due to

four multi-country studies (Abdulkadri et al., 2009; Barceló et al., 2003; Boutayeb et al., 2014; Jönsson, 2002), estimating costs for multiple countries. The USA was the most studied country (n=19), followed by Canada (n=7) and Germany (n=5). Mexico (n=6) and China (n=4) were the most frequently studied LMICs.

Data sources

Especially in LMICs, self-administered surveys represented a popular method to retrieve data on the cost of diabetes. These were mostly limited regionally, i.e. to a city or hospital, and usually only representative of these regional populations with diabetes but not of a national population. In HICs, databases of insurance and healthcare providers were the main source of information in most studies. These data tended to be representative either at a national or at some sub-national level. As a result, the size of the samples in HICs was mostly between 1,000 and several million. By contrast, studies in low- and lower-middle-income countries were generally characterized by smaller sample sizes, ranging from 35 (Suleiman et al., 2006) to about 2,433 (Yang et al., 2012) in the studies reviewed here.

Variation in costing approaches

As discussed in more detail in Text Box 1, a range of costing approaches are used in the COI literature. Figure 2 shows that the most common costing method for the direct costs of diabetes in HICs was the sum-all medical approach for people with diabetes without using control groups (Arredondo et al., 2007; Arredondo et al., 2005; Arredondo et al., 2011b, 2004; Barceló et al., 2003; Bjegovic et al., 2007; Boutayeb et al., 2014; Brandle et al., 2003; Camilo González et al., 2009; Chi et al., 2011; Condliffe et al., 2014; Horak, 2009; Jönsson, 2002; Kirigia et al., 2009; Lau et al., 2011; Lee et al., 2006; Lucioni et al., 2003; Maciejewski et al., 2004; Martin et al., 2007; Morsanutto et al., 2006; Nakamura et al., 2008; Nolan et al., 2006; Ohinmaa et al., 2004; Oliva et al., 2004; Peele et al., 2002; Pohar et al., 2007b; Redekop et al., 2002; Ringborg et al., 2008; Zhou et al., 2005).

The disease-attributable costing approach (Abdulkadri et al., 2009; Ballesta et al., 2006; Bastida et al., 2002a; Buescher et al., 2010; Dall et al., 2003; Davis et al., 2006; Honkasalo et al., 2014; Johnson et al., 2006; Lin et al., 2004; Mata et al., 2002; Rodríguez Bolaños et al., 2010; Simpson et al., 2003; Solli et al., 2010; Suleiman et al., 2006; Tunceli et al., 2010) and the attributable-fraction approach were also used widely, though mainly in the USA (Bolin et al., 2009; Dall et al., 2008; Dall et al., 2010; Dawson et al., 2002; Honeycutt et al., 2009; Leśniowska et al., 2014; Schmitt-Koopmann et al., 2004).

The incremental cost approach was applied primarily in studies on HICs (Birn-

baum et al., 2003; Bruno et al., 2012; Chodick et al., 2005; Durden et al., 2009; Esteghamati et al., 2009; Honeycutt et al., 2009; Köster et al., 2006, 2011; Köster et al., 2012; Linden et al., 2009; Marchesini et al., 2011; Norlund et al., 2001; O'Connell et al., 2012; Pohar et al., 2007a; Ramsey et al., 2002; Ricordeau et al., 2003; Rodbard et al., 2010; Smith-Spangler et al., 2012; Trogdon et al., 2008; Tunceli et al., 2010; Wirhn et al., 2008; Yang et al., 2012).

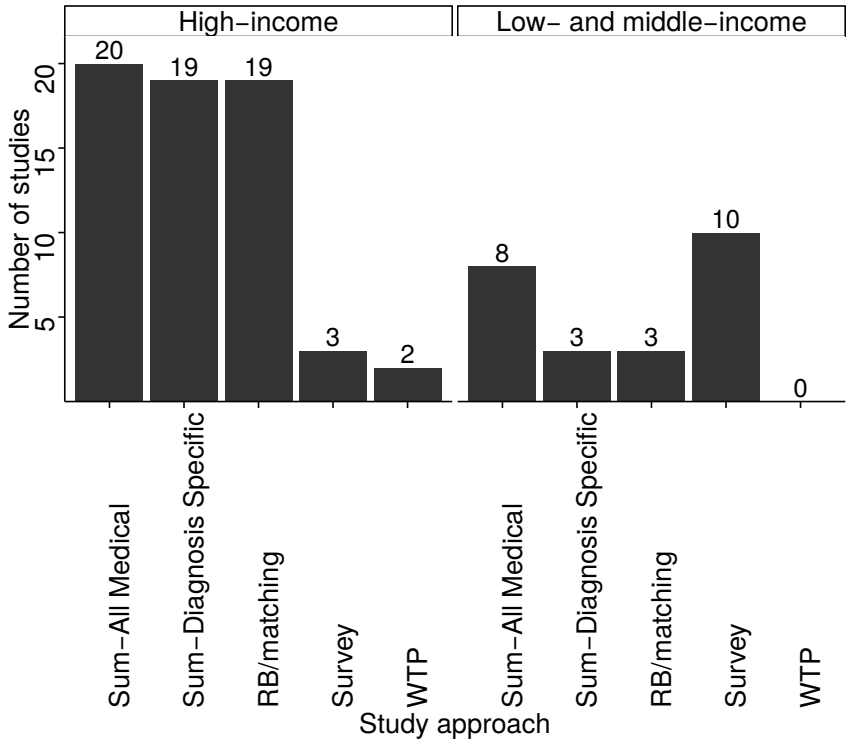
For LMICs, the survey approach was the most used (Biorac et al., 2009; Chan et al., 2007; Chatterjee et al., 2011; Druss et al., 2001; Elrayah-Eliadarous et al., 2010; Javanbakht et al., 2011; Khowaja et al., 2007; Al-Maskari et al., 2010; Ramachandran et al., 2007; Tharkar et al., 2010; Wang et al., 2009a, 2010, 2009b).

By contrast, almost all indirect cost assessments followed the same methodology, i.e. the human capital approach. This approach considers all forgone labour earnings of a patient or caregiver that are attributable to diabetes. A minority of three studies (Chang, 2010; Gyldmark et al., 2001; Tharkar et al., 2010), estimated the indirect costs using the WTP approach, which tries to measure how much individuals would be willing to pay to reduce the risk of an illness (Segel, 2006), here diabetes (or certain complications associated with it). One of the studies included WTP estimates in addition to the direct and indirect costs measured by the human capital approach (Tharkar et al., 2010), but did not include the WTP estimate in the overall cost estimate, while the other two studies estimated exclusively the WTP (Chang, 2010; Gyldmark et al., 2001).

Study perspective

Studies also varied in their perspective, again compromising direct comparability of the cost estimates across studies. Overall, most studies either took a societal (n=32) or healthcare system perspective (n=48). The former generally takes into account the direct and indirect monetary costs that arise to society, including costs to the healthcare system, costs due to lost productivity and sometimes OOP costs (Segel, 2006). The latter was especially common in HICs where many studies assessed the cost of diabetes to private or public health insurances. In LMICs, studies often took the patient perspective (n=5), estimating OOP expenditures and in some cases productivity losses, directly arising to the diabetes patient.

Figure 2: Number of COI studies, by costing approach and income group.



Notes For LMICs no willingness to pay (WTP) study is counted, because the only study (Tharkar et al., 2010) presenting a WTP estimate for a LMIC used primarily a different approach to estimate costs, and the WTP estimate was only presented additionally. Therefore this study was not counted under WTP here. Two studies are counted twice as they give estimates for a sum-diagnosis specific and a RB/matching approach.

Text box 1 COI methodologies

Methodologies for COI studies can broadly be categorized into two main categories:(1) estimating the total disease costs and (2) estimating the incremental costs (Akobundu et al., 2006). Studies can then be divided further according to the specific approach used for estimation. Our categorization builds on that by Akobundu et al. (2006) in their review of COI methodologies.

1. Total disease costs
    a) Sum-All Medical: captures all medical expenditures of a person diagnosed with diabetes, irrespective of the relation of the expenditures with diabetes.
    b) Sum-Diagnosis Specific: includes the costs that are related to diabetes. This can be done by using a disease-attributable costing approach, using administrative claims databases to identify the cost of diabetes by respective International Statistical Classification of Diseases and Related Health Problems (ICD) codes that link the expenditures to a primary or secondary diagnosis of diabetes as the reason for the healthcare utilization. Alternatively, a similar technique used at the population level is the attributable-fraction approach, where the relative contribution of, e.g. diabetes, to the risk of developing another disease (e.g. renopathy or cardiovascular disease) is used to determine how much of the costs of this disease can be attributed to diabetes.
    c) Survey approach: while not specifically mentioned by Akobundu et al. (2006), for this review we create a separate category capturing studies using surveys of people with diabetes. This category differs from the two approaches a) and b) above in that estimations rely solely on the individual, reported experience of people with diabetes, without use of any diagnostic data at an aggregate level. The survey approach was also used as a separate category in the earlier review on diabetes COI studies by Ettaro et al. (2004).
2. Incremental disease costs

    There are two main approaches for the estimation of incremental medical costs:
    a) Regression approach: a statistical technique which can account for observable differences between the group with diabetes and the control group (i.e. those without diabetes) to find—ideally—the independent effect of diabetes on healthcare costs. The differences typically accounted for are age, region and gender.
    b) Matching approach: uses a control group to directly compare those with diabetes to those without diabetes after matching each person of the 'treatment' group to a 'similar' person of the control group, using various categories like age, region and gender to—again—find the independent effect of diabetes on healthcare cost (Akobundu et al., 2006).

All of the above approaches can be used in prevalence or an incidence based study. In the former case the costs of diabetes are estimated for a certain point in time, typically one year, while the latter approach estimates costs over a person's lifetime or several years, always starting with the point at which the disease is diagnosed. Both approaches may also be combined in studies estimating the future cost burden of type 2 diabetes by first taking a prevalence approach to calculate current costs and then using predictions about future diabetes incidence rates to arrive at an estimate of diabetes costs at a certain point in the future.

Costing components

Of the 75 studies that reported the cost components they used to estimate direct costs, 72 took into account outpatient hospital visits, 70 inpatient hospital visits, 63 physician visits, 58 drug costs, 51 laboratory costs for diagnostic tests and check-ups, 37 equipment costs and 21 non-medical and transportation costs. A total of 46 studies had at least included the costs of hospital, outpatient and physician visits as well as drugs (see Table A4 for a detailed description of cost components used in each study).

Cost estimates of diabetes using a prevalence approach

Two basic epidemiological approaches exist for the estimation of COI, and they are not directly comparable. The incidence approach follows people with diabetes, usually starting with their diagnosis at a common base year, estimating yearly costs for a sample of people at the same disease stage, finally giving an estimate of diabetes costs over a certain time period, such as from diagnosis to death or over a distinct period of, for example, 10 years. This approach can also document how costs of diabetes change and develop over the progression of the disease (Larg et al., 2011). By contrast, the prevalence approach estimates the costs of diabetes for a cross-section of people with diabetes at a certain point in time, normally a year, who are at different stages of the disease. It is most suitable for assessing the total economic burden of diabetes at a certain point in time. Due to this difference in time periods and the data used, the estimates of prevalence-based studies are not directly comparable with those of incidence-based studies. Hence, we present the cost estimates, starting with the prevalence approach.

Table 2 shows the range of direct cost estimates by estimation approach and income status. As can be observed, direct cost estimates varied widely, both between and within the different estimation approaches. Cost estimates for direct costs, irrespective of the costing method applied and the cost components included, ranged from $242 for Mexico (Arredondo et al., 2005) in 2010 to $11,917 for the USA (Condliffe et al., 2014) in 2007. Also, studies from LMICs generally indicated smaller direct costs than studies from HICs.

For indirect costs, studies using the human capital approach estimated costs ranging from $45 for Pakistan (Khowaja et al., 2007) in 2006 to $16,914 for the Bahamas (Barceló et al., 2003) in 2000. Three studies estimated indirect costs by using the WTP approach and found costs ranging from $191 in a study on the WTP for a health insurance for type 2 diabetes in Denmark in 1993 (Gyldmark et al., 2001), a WTP $4,004 per year for a cure of type 2 diabetes (Chang, 2010) in Taiwan and an annual payment of $4,737 to halt disease progression/prevent future complications of diabetes in India (Tharkar et al., 2010).

Societal costs of type 2 diabetes, which are estimated by studies combining direct and indirect costs, ranged from $544 in a study on the economic costs of diabetes in Iran (Esteghamati et al., 2009) in 2001 to $18,224 for the Bahamas (Barceló et al., 2003) in 2000.

In order to improve the cross-country comparability of the costs of diabetes we plotted the results from studies providing a direct per capita cost estimate against the GDP per capita estimate of the respective country (we limited this comparison to studies using samples representative of their entire population). Figure 3 confirms the expectation that costs do increase with economic wealth: GDP per capita explains about one-third of the variation in cost estimates (see r2 in Figure 3). Also, studies on the USA seem to estimate costs consistently higher than would be expected on the basis of its GDP per capita.

The USA, however, spend consistently more than what would be expected on the basis of its GDP per capita. Again, the wide variation in estimated costs for many countries underscores the point that the studies need to be contextualized and may not be directly comparable per se. On the whole—though by no means always—the matching and regression as well as the sum-diagnosis specific approaches appear to produce lower cost estimates than especially the total cost results, particularly so for HICs. In an inevitably crude attempt to quantitatively explore the driving factors behind the heterogeneity in cost estimates, we estimated a simple linear regression model with per capita direct costs as the dependent variable; explanatory variables included GDP per capita, the estimation approach employed by the study, the number of included cost components, a dummy for studies carried out in the USA, the year of data collection, the representativeness of the study and if the study included diabetes complications as explanatory variables. The results, displayed in Table 2, show a strong relationship between GDP per capita and expenditures for diabetes, with every additional international dollar in per capita GDP translating into an average increase in direct diabetes expenditures of about $0.04. The estimation approach is not found to matter significantly, nor is the year of study. Estimates from USA studies put the costs at over $3,000 higher (on average) than studies from other countries, indicating that costs in the USA may indeed be unusually high. The number of costing components and the inclusion of complications likely also explain some of the variance in estimates, although they are just below and above the 10% significance level, respectively. Overall, the included independent variables explain about 56% of the variation in direct cost estimates. In a sensitivity analysis, we included the results from multi-country studies providing country estimates in the regression analysis. The only major difference to the presented analysis is that the inclusion of complications as well as the number of included cost components were now significant at the 1% and 5% significance level, re-

Table 1: Summary of direct costs by estimation approach and income status in international dollars $ (2011) for prevalence-based studies.

	High-income countries				Low- and middle-income countries			
	Sum-all medical costs	Sum-diagnosis specific	RB / matching	own survey	Sum-all medical costs	Sum-diagnosis specific	RB / matching	own survey
Min	1117	907	264	1495	242	662	443	456
Max	11917	9346	8306	5585	4129	4672	1136	3401
N	25[a]	19[a]	18	3	27[a]	5[a]	2	10

Notes [a] Includes country estimates from multi-country studies; RB Regression based

spectively. The effect size and significance of the other estimates did not change considerably.

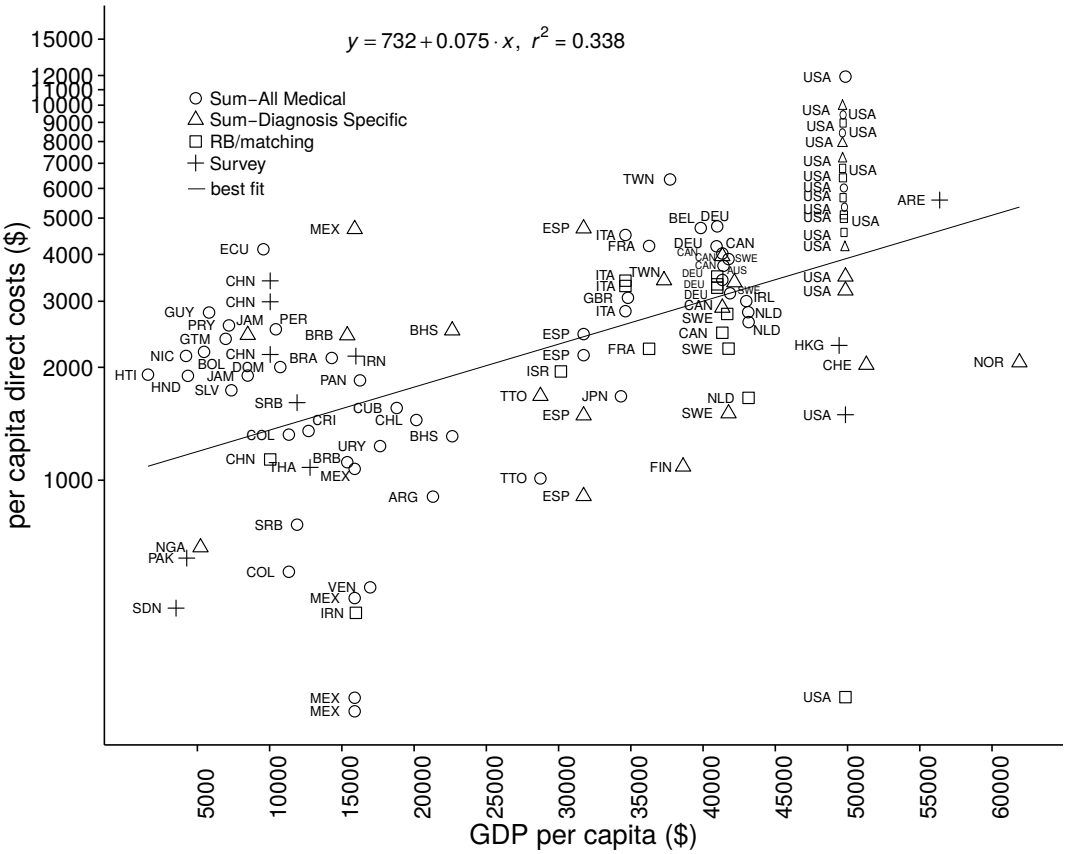
The sensitivity of the cost results to the estimation approach was also examined by two studies that investigated the effect of different estimation techniques in diabetes COI studies. Honeycutt et al. (2009) compared the use of a regression-based and an attributable-fraction approach and found that the cost estimate of the former exceeded the latter by 43%. Tunceli et al. (2010) compared the matching and the diabetes (disease)-attributable costs approach and found a 14–29% higher cost estimate using matching, depending on the assumptions used. Both studies concluded that an incremental cost approach results in a higher, and likely more exact, estimate of the direct costs of diabetes than disease-attributable approaches. The authors attributed this to the fact that a regression or matching approach can assign costs to diabetes that cannot be linked to diabetes otherwise. Those approaches are therefore in a position to account for all costs of co-morbidities caused by diabetes, while this is not automatically the case with the other approaches.

Direct and indirect costs of diabetes

Comparing the relative importance of direct and indirect costs across countries may provide some information regarding the underlying drivers of costs due to diabetes in different countries. For instance, a higher ratio of direct to indirect costs may indicate that the higher direct expenditures have led to better treatment and less complications and thereby have reduced the productivity losses due to diabetes. We therefore plotted direct against indirect costs from studies that provided both estimates and drew a 45°line depicting the equal share of direct and indirect costs (see Figure 4). Studies above the line found higher direct costs compared to indirect costs and studies below the line found higher indirect costs compared to direct costs.

Most studies found a larger share for direct costs in comparison with indirect costs. This is especially true for HICs, where only a study on Sweden (Bolin et al., 2009) found a larger share for indirect costs. For LMICs, a study on Colombia (Camilo González et al., 2009) found considerably higher indirect costs, as did the multi-country study of Barceló et al. (2003) and a study on various countries in the African region (Kirigia et al., 2009), which both found higher indirect costs for almost every country in the study and also on average for the entire region, represented as the mean overall study estimate in Figure 4. Both studies used similar approaches to estimate costs, and indirect cost estimates were likely so high because evidence from only a few countries within the region was used as a basis for estimating indirect costs for every other country in the respective study.

Figure 3: GDP to direct costs ratio by estimation approach.



Notes The line depicts the best fit based on the linear regression of direct costs on GDP per capita in international dollars.

Table 2: Relationship between direct costs and study characteristics (robust linear regression).

	Estimate	Std. Error
Constant	2133	1773.922
GDP per capita ($)	0.045**	0.017
Estimation Approach		
Sum-All medical (Ref.)		
Sum-Diagnosis Specific	−413.880	528.766
RB/matching	−719.868	526.896
Survey	−689.806	671.020
At least four costing components	702.966*	403.968
USA study	3111.067***	533.534
Year of study		
<1995 (Ref.)		
1995-1999	−1744.799	1632.498
2000-2004	−816.647	1586.966
2005-2009	−1021.685	1592.595
2010-2014	−2744.739	1839.689
Study representative	−598.670	409.070
Complications	666.803	414.727
R-squared adj.	0.559	
N	70	

Notes Standard errors in parenthesis. Ref. reference category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Further, the studies took the countries' per capita gross national product as a proxy for earnings, which might have led to an over-estimation of the indirect costs (Kirigia et al., 2009).

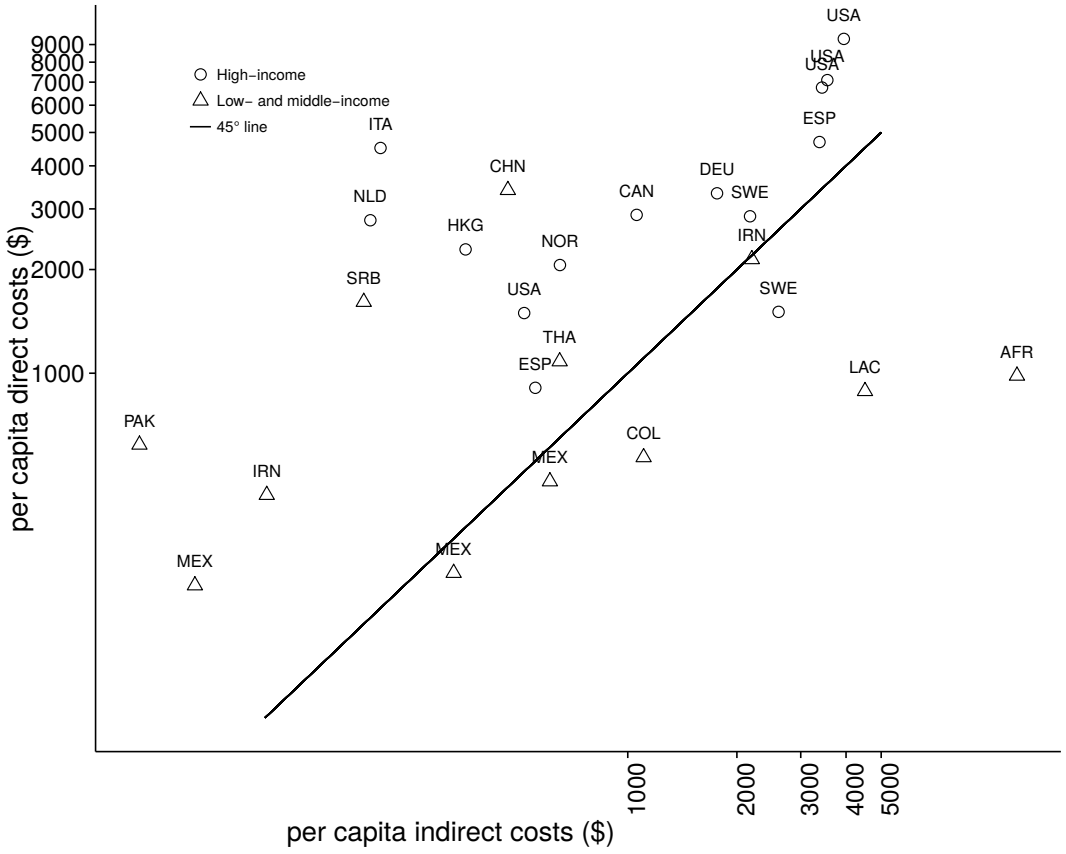
Overall, no clear pattern emerges that would indicate that in LMICs indirect costs would be higher than direct costs due to their less extensive healthcare systems, or that HICs would be able to prevent indirect costs as a result of their higher healthcare spending. For instance, while some studies indicated that middle-income countries (MICs), such as Colombia and Mexico, have higher indirect costs, studies on China, Pakistan and, again, Mexico showed the opposite. Difficulties in measuring costs could be one of the main reasons for the heterogeneity in results even for the same country and may make a comparison of direct and indirect costs difficult. In particular in LMICs, direct healthcare expenditures may be low due to limited availability and access to healthcare, hence direct costs would be higher if more treatment options were available. Indirect costs may also be incorrectly measured, for example the use of the human capital approach—which estimates the potential instead of the actual lost production, e.g. assuming that a sick individual cannot be replaced by a previously unemployed individual, even though in reality production losses may only be temporary until the employer has found a replacement—may lead to an overestimation of the losses in productivity (Segel, 2006).

Studies using the incidence approach

The four studies that used an incidence approach (see Table 3) estimated the cost of diabetes either over a person's lifetime (Birnbaum et al., 2003; Camilo González et al., 2009) or over a certain period after diagnosis (Johnson et al., 2006; Martin et al., 2007). Camilo González et al. (2009) modelled the lifetime (direct and indirect) costs of a typical diabetes patient in Colombia, arriving at a mean cost estimate of $54,000. The second study providing lifetime estimates by Birnbaum et al. (2003), estimated incremental lifetime healthcare costs for USA females with diabetes of $283,000.

Two studies followed patients over a limited time period and found different patterns in the development of type 2 diabetes-attributable healthcare costs. In Germany costs increased from $1634 in the first year after diagnosis to $4881 in the seventh year (Martin et al., 2007). In Canada, Johnson et al. (2006) found the highest costs in the year of diagnosis with $7635, up from $2755 the year prior to diagnosis. In the year after diagnosis costs decreased to $4273 and then only increased slightly to $4618 in year ten. In Germany and Canada, costs related to complications or hospital visits were the most important components and in Germany increased steadily over time. In Canada costs related to prescriptions

Figure 4: Direct and indirect cost relation in studies estimating total costs of type 2 diabetes.



Notes The 45°line depicts the points where direct and indirect costs would be equal. Above the line direct costs are higher than indirect costs and vice versa. For better visibility both coordinate axes are expressed in log scale

increased the most.

Table 3: Incidence studies on the costs of diabetes

Ref.	Country	Time horizon	Population	Approach	Results
Johnson et al. (2006)	Canada	1992–2001	Incidence T2D patients from Saskatchewan Health's administrative database in Canada	Sum-all medical	Highest total healthcare costs at year of diagnosis with CAN$7343 ($7635), then increased from a low of CAN$3880 ($4034) 3 years after diagnosis to CAN$4441 10 years thereafter ($4618).
Camilo González et al. (2009)	Colombia	32 years	Hypothetical average Columbian T2D patient	Sum-all medical	Total lifetime costs (32 year period) of average diabetes patient, including direct and indirect costs, 57.565 million Colombian pesos ($54,351).
Martin et al. (2007)	Germany	1995–2003	Newly diagnosed T2D patients from randomly drawn practices across Germany	Sum-all medical	EUR 1,288 ($1635) for the first treatment year after diabetes diagnosis and increased to EUR 3845 ($4880) in the seventh year.

Table 3: Incidence studies on the costs of diabetes

Ref.	Country	Time horizon	Population	Approach	Results
Birnbaum et al. (2003)	United States	1997–1998	Women employed by nationwide operating company and hypothetical women above age 64 receiving Medicare	RB / matching	$282973 incremental lifetime direct healthcare costs, using incidence-based, steady-state methodology.

T2D type 2 diabetes

Country level costs prediction studies

Four studies projected costs of diabetes over a certain period of time (Davis et al., 2006; Lau et al., 2011; Ohinmaa et al., 2004; Wang et al., 2009b), making assumptions about the future development of diabetes prevalence and population ageing (see Table 4). For Canada, a 1.7-fold increase from 2000 to 2016 (Ohinmaa et al., 2004) and a 2.4-fold increase from 2008 to 2035 in diabetes healthcare costs was estimated (Lau et al., 2011). Taking a healthcare system perspective, both studies found that the estimated increase would be mostly driven by an ageing population. For Australia, Davis et al. (2006) estimated a 2.5- to 3.4-fold increase in diabetes attributable healthcare costs from 2000 to 2051, depending on the underlying assumptions about population ageing and diabetes prevalence rates. For China, Wang et al. (2009b) extrapolated total costs of diabetes from the year 2007 to 2030, estimating the costs of diabetes to increase 1.8-fold, solely accounting for the expected increase in prevalence.

The impact of diabetes on employment probabilities and productivity

Besides studies that determined the cost of diabetes by costing related expenditures, another body of research has investigated—using econometric techniques—the impact of diabetes on 'productivity', a term used here to comprise outcomes including employment probabilities and lost work days and income or earnings. A recent study systematically reviewed evidence on the impact of diabetes on the ability to work, focusing on studies assessing the impact of diabetes on early retirement, lost work hours, absenteeism and presenteeism (Breton et al., 2013). We focused particularly on studies exploring the impact of diabetes on employment probabilities and earnings—both issues that were not covered in the mentioned review—and we took a more detailed look at the empirical challenges posed by the issue of endogeneity (see page 215 in the Appendix for a more detailed discussion of endogeneity).

Tables 5 and 6 synthesize the relevant information from the 23 identified studies on the effect of diabetes on employment and other labour market outcomes. Almost all studies were conducted on HICs, mainly the USA (n=13) and European countries (n=4). Only one study focused on a LMIC investigating the effect of diabetes on labour income in China.

Employment probabilities

Most studies examined the impact of diabetes on employment probability (n=17), applying a range of econometric techniques. These have evolved over time, and

Table 4: Country level costs prediction studies

Ref.	Country	Population	Approach	Time horizon	Results
Davis et al. (2006)	Australia	Australian population	Sum diagnosis Specific	2000–2051	If age and sex specific prevalence remains unchanged a 2.5-fold increase; if age and sex specific prevalence allowed to change as well a 3.4-fold increase.
Ohinmaa et al. (2004)	Canada	Canadian population	Sum-all medical costs	2000–2016	1.7-fold increase.
Lau et al. (2011)	Canada	Four Alberta Health and Wellness databases	Sum-all medical costs	2008–2035	2.4-fold increase.
Wang et al. (2009b)	China	In patients and outpatients in 20 hospitals	Own survey	2007 and 2030 (projection)	Increase from $73 billion in 2007 to $132 billion in 2030 (1.8 fold increase).

more recent studies took into account the possibility that diabetes might be endogenous: it is conceivable that especially personal traits such as motivation and drive could influence the propensity to develop type 2 diabetes as well as a persons' job market opportunities. Further, being employed or unemployed could also lead to changes in lifestyles, due to changes in income, stress or leisure time, that could themselves affect the chances of developing diabetes (Brown et al., 2005b). Of the studies that tried to account for this problem (Brown et al., 2005b; Harris, 2009; Latif, 2009; Lin, 2011; Minor, 2011; Zhang et al., 2009), the majority used an instrumental variable (IV) technique. This approach allows for the consistent estimation of the effect of diabetes on employment if a variable can be found that is causally related to diabetes without affecting the employment probabilities through any other unobserved pathway apart from its effect on diabetes (see Text Box 1). In the case of type 2 diabetes, all studies used the family history of diabetes as an IV to exploit the fact that the development of type 2 diabetes is much more likely for individuals whose biological parents have also had diabetes. It is argued that, while controlling for education, age and other observable demographic and socioeconomic factors (e.g. wealth, regional and ethnic differences and the number of children in the household), having a family member with diabetes should not affect the person's employment status or other labour market outcomes, while strongly predicting the onset of type 2 diabetes.

Table 5: Studies estimating the relationship between diabetes and employment (2001 – 2014)

Ref	Survey year	Country	Age	Effect on employment	
				Males	Females
Harris (2009)	1999-2000	Australia	>24	Exogenous: 10.8 percentage points reduction to be in labour force; endogenous: 7.1 percentage points reduction and test indicates endogeneity.	Exogenous: 10 percentage points to be in labour force; endogenous: Nine percentage points reduction and test indicates endogeneity
Zhang et al. (2009)	2001, 2004-2005	Australia	18-64	50-64: 11.5 percentage points less likely to be in labour force; 18-49: 3.9 percentage points less likely, all effects increase when other chronic diseases are present.	No significant effect for diabetes alone; significant negative effect if other chronic diseases are present.
Latif (2009)	1998	Canada	15-64	Exogenous: 19 percentage points less likely to be employed; endogenous: not significant and positive and test indicates endogeneity.	Exogenous: 17 percentage points less likely to be employed, endogenous: not significant and positive and test indicates exogeneity.
Kraut et al. (2001)	1983-1990	Canada	18-64	With complications 2 times less likely to be in labour force; no significant effect on employment for those in labour force.[a]	

Table 5: Studies estimating the relationship between diabetes and employment (2001 – 2014)

Ref	Survey year	Country	Age	Effect on employment	
				Males	Females
Norlund et al. (2001)	1992-1993	Sweden	>24	14.2 percentage points higher retirement rate (22.9 compared to 8.7).[a]	
Alavinia et al. (2008)	2004	Sweden, Denmark, Netherlands, Germany, Austria, Switzerland, France, Italy, Spain, Greece	50-65	For whole dataset: no effect of diabetes on being unemployed, but increased odds ratio of 1.33 on being retired. No information on effects by country.[a]	
Lin (2011)	2005	Taiwan	45-64	Exogenous: 9 percentage points less likely to be employed; endogenous: 19 percentage points less likely to be employed; test on whole sample indicates endogeneity.	Exogenous: 11 percentage points less likely to be employed, endogenous: not significant and negative.

Table 5: Studies estimating the relationship between diabetes and employment (2001 – 2014)

Ref	Survey year	Country	Age	Effect on employment	
				Males	Females
Brown et al. (2005b)		USA	>44	Exogenous: 7.4 percentage points less likely to be employed; endogenous: 10.6 percentage points less likely but test indicates exogeneity.	Exogenous: 7.5 percentage points less likely to be employed; Endogenous: no significant effect found and test indicates endogeneity.
Minor (2011)	2006	USA	>19 at diagnosis		Exogenous: 25.2 percentage points less likely to be employed, endogenous: 45.1 percentage points less likely to be employed.
Vijan et al. (2004)	1992-2000	USA	51-61	More likely to be retired in 1992 (adjusted OR 1.3). Over 8 years follow up spent 0.14 incremental years in retirement.[a]	
Bastida et al. (2002a)	1996-1997	USA	>44	7.5 percentage points less likely to be employed.	No significant effect on employment probabilities found.

Table 5: Studies estimating the relationship between diabetes and employment (2001 – 2014)

Ref	Survey year	Country	Age	Effect on employment	
				Males	Females
Brown et al. (2011)	2008	USA	35-64	Diabetes negatively related to employment (5 percentage points reduction); better diabetes management (HbA1c) positively affects employment probabilities; HbA1c lowering of 10% increases employment probability by 0.44 percentage points.	No significant effect on employment probabilities found.
Tunceli et al. (2005)	1992,1994	USA	51-61	9 percentage points less likely to work without complications controlled for, with complications controlled for 7.1 percentage points less likely.	5.9 percentage points less likely to work without complications controlled for, with complications controlled for 4.4 percentage points less likely but not significant.

Table 5: Studies estimating the relationship between diabetes and employment (2001 – 2014)

Ref	Survey year	Country	Age	Effect on employment	
				Males	Females
Tunceli et al. (2009)	1997-2005	USA	20-44 and 45-64	20-44: proportion with work limitations 3.1% higher; 45-64: proportion not working is 8.1% higher; the proportion work disabled is 3.4% higher; proportion with work limitations is 5.7% higher (all compared to similar age group without diabetes).[a]	
Valdmanis et al. (2001)	1990-1995	USA		Unemployment rate for persons with diabetes was 16% compared with 3% among matched comparison group.[a]	
Ng et al. (2001)	1989	USA	>29 at diagnosis	3.6% less likely of being employed (exogenous), 12% for those with complications.[a]	
Minor (2013)	1979-2010	USA	>14	Average reduction of employment probability of 28 percentage points; strongest employment penalty in first 5 years after diagnosis.	Average reduction of employment probability of 36 percentage points; strongest employment penalty in first 15 years after diagnosis.

[a] No gender differentiation in study

Because IV estimation has worse asymptotic properties than single equation regression results when endogeneity is not an issue, studies tested for the existence of endogeneity to determine which results to rely on for inference (Brown et al., 2005b; Latif, 2009; Lin, 2011; Minor, 2011). Interestingly, the reviewed studies found diabetes to be endogenous for either males (Latif, 2009) or females (Brown et al., 2005b; Minor, 2011), but never for both. Further, the use of an IV sometimes increased the estimated effect (Lin, 2011; Minor, 2011) whereas in other cases the effect turned insignificant (Brown et al., 2005b; Latif, 2009). As a result, no unambiguous conclusions can be drawn as to how endogeneity affects diabetes and whether or not it causes biased estimates. Most of the relevant studies also explored whether accounting for body mass index (BMI) or other diabetes-related chronic conditions would substantially alter the result and found this not to be the case (Brown et al., 2005b; Latif, 2009; Minor, 2013).

Overall, studies more commonly found a significant adverse impact of diabetes on males, ranging from no effect in Canada (Latif, 2009) to a 19 percentage point reduction in Taiwan (Lin, 2011). Conversely, no effect was found for women in Taiwan (Lin, 2011), Australia (Zhang et al., 2009) or for Mexican Americans in Texas (Brown et al., 2005b). However, a 45% decrease in employment probabilities was observed for women in the USA (Minor, 2011). Extending the scope and looking at how diabetes duration affected labour market outcomes, using pooled longitudinal data from the USA, one study found that the main adverse effect on employment probabilities materialized within the first 5 years after diagnosis for men and 11–15 years after diagnosis for women (Minor, 2013).

Productivity

For earnings, no effect was found for Mexican-American men in Texas (Bastida et al., 2002a), while the highest loss was found for women in the USA ($21,392 per year) (Minor, 2011). Again looking at diabetes duration, a wage penalty was only found for USA men 6–10 years after diagnosis, reducing their wage by about 18 percentage points (Minor, 2013). The only study on a non-HIC, China, tried to tease out the psychological effect of a diabetes diagnosis on subsequent labour income, finding a reduction of 22% in income for males, but not for females. Further, those with an HbA1c between 8–10% experienced the most severe income penalty (29%). The study further showed that the adverse effect of a diabetes diagnosis was concentrated among the poorest third of the study population (Liu et al., 2014). Another study investigated the effect on earning losses for caregivers of people with diabetes in the United Kingdom (UK), finding a reduction of $2,609 per year, while the person with diabetes experienced a loss of $1,744 per year (Holmes et al., 2003). For income, a reduction of $6,250 per year was found

for older USA adults who had been followed between the years 1992 and 2000 (Rivera et al., 2004). In terms of lost workdays and work hours due to diabetes, the effects ranged from no impact on lost work days on older people (Rivera et al., 2004) and females in the USA (Minor, 2011) to 3.2 lost work days in a USA population within a 2-week period if complications were present (Ng et al., 2001).

In terms of the methodology used, these studies tended to rarely account for endogeneity, and they mostly used standard regression or matching methods to estimate the impact of diabetes. Three studies (Bastida et al., 2002a; Brown et al., 2011; Minor, 2011) corrected for the possibility of a sample selection bias, to account for systematic differences between the working population and the overall population. Only one study additionally applied IV methods and found diabetes to be endogenous, so that its effects on earnings were dramatically understated using naive regression results (Minor, 2011). For working hours and days missed due to illness, the same study found no indication of endogeneity. Only one study applied an approach other than IV to account for endogeneity, using a difference-in-difference model and exploiting a recent diagnosis of diabetes, which was the result of the collection of biomarkers in the survey used, as a natural experiment to measure how income developed between those who were newly diagnosed and those without diabetes in the years following diagnosis (Liu et al., 2014).

Table 6: Studies estimating the relationship between diabetes and other productivity outcomes (2001 – 2014)

Ref.	Survey year	Country	Age	Effect on other productivity outcomes	
				Males	Females
Kraut et al. (2001)	1983–1990	Canada	18–64	Effect on earnings only when complications are present: reduced to 72% of total income of controls.a	
Liu et al. (2014)	2009, 2011	China	not given	16.3% decrease in annual income; strongest effect for those in lower income quintiles.[a]	
Herquelot et al. (2011)	1989–2007	France	Male 40–50, females 35–50 in 1989	1.7 HR to transition from employed to disabled, 1.6 HR to be retired, 7.3 HR to be dead; between age 35 and 60 each person with diabetes lost 1.1 years of time in workforce.[a]	
Leijten et al. (2014)	2010–2013	Netherlands	45–64	Diabetes reduced work ability measured using Work Ability Index (WAI) by 2%. No significant effect on productivity was found.[a]	
Norlund et al. (2001)	1992–1993	Sweden	>24	9.4 more sick days.[a]	
Holmes et al. (2003)	1999	UK	<65	GBP 869 lost earnings per year with diabetes; GBP 1300 for carers of people with diabetes.[a]	

Table 6: Studies estimating the relationship between diabetes and other productivity outcomes (2001 – 2014)

Ref.	Survey year	Country	Age	Effect on other productivity outcomes	
				Males	Females
Minor (2011)	2006	USA	>19 at diagnosis		Exogenous: $2865 loss in earnings per year, Endogenous: $19655; Exogenous: 2 working hours less per week, no significant effect on missed workdays per year, endogenous: no significant effect on working hours or workdays missed.
Vijan et al. (2004)	1992–2000	USA	51–61	Lost income of $50004 from 1992–2000 per capita or $6250 per year, for whole USA population of same age $85.6 billion or $10.7 billion per year; people with diabetes more likely to have taken sick days in 1992 (adjusted OR 1.3).[a]	
Collins et al. (2005)	2002	USA	working age	No significant effect on work days.[a]	
Bastida et al. (2002a)	1996–1997	USA	>44	No significant effect on earnings.	Women with diabetes earn 84% less.

Table 6: Studies estimating the relationship between diabetes and other productivity outcomes (2001 – 2014)

Ref.	Survey year	Country	Age	Effect on other productivity outcomes	
				Males	Females
Brown et al. (2011)	2008	USA	35–64	Wages reduced by 0.74% due to diabetes; for every 10% reduction in HbA1c wages rise by 0.62%. HbA1c >8 was related to decreasing wages.	No significant effect of diabetes on female earnings; no effect of blood sugar management for women, HbA1c levels just below 6 to just above 7 were related to lower wages.
Lenneman et al. (2011)	2005–2009	USA	>16	Lost earnings per year of $2146.[a]	
Tunceli et al. (2005)	1992, 1994	USA	51–61	No significant effect on number of work days.	2.5 more lost workdays per year.
Valdmanis et al. (2001)	1990–1995	USA		71% of the persons with diabetes had an annual income of less than $20000 compared with 59% of the matched respondents.[a]	
Ng et al. (2001)	1989	USA	>29 at diagnosis	No significant effect on work days for T2D, for those with complications 3.2 days lost within two weeks	

Table 6: Studies estimating the relationship between diabetes and other productivity outcomes (2001 – 2014)

Ref.	Survey year	Country	Age	Effect on other productivity outcomes	
				Males	Females
Brown et al. (2005a)	NA	USA	>45	For every dollar of labour income lost by adults with diabetes, a further income reduction of $0.48 occurs in the community. Total output reduction for upper bound estimate is $300 million for the local economy.[a]	
Minor (2013)	1979–2010	USA	>14	No general effect of type 2 diabetes on wages; some evidence of wage penalty of about 18% 6–10 years after diagnosis	No strong evidence found for wage penalty for females

Notes T2D type 2 diabetes [a] No gender differentiation in study

Discussion

The objectives of this systematic review were to identify new evidence on the economic impact of type 2 diabetes that emerged since 2001 and extend the scope of the review by including studies on the labour market impact of diabetes. We identified studies from a great variety of countries, with large differences in cost estimates across and within countries.

General findings and developments since the 2004 review of diabetes COI studies

An obvious development since the last review is the emergence of COI studies on LMICs. The economic burden related to diabetes found in these studies indicated a strong direct impact on those affected by diabetes. This is reflected in the substantial burden of OOP treatment costs incurred by patients (Arredondo et al., 2007; Chatterjee et al., 2011; Elrayah-Eliadarous et al., 2010; Esteghamati et al., 2009; Khowaja et al., 2007; Ramachandran et al., 2007; Smith-Spangler et al., 2012; Suleiman et al., 2006; Tharkar et al., 2010; Wang et al., 2009a, 2010), with considerable proportions of the annual income being spent on diabetes care. This relative cost burden was generally higher for people with relatively lower household incomes (Khowaja et al., 2007; Ramachandran et al., 2007; Tharkar et al., 2010). Health insurance coverage had some protective effects against OOP expenditures, but mainly for those with higher incomes, while the poor often lacked coverage (Khowaja et al., 2007; Ramachandran et al., 2007; Tharkar et al., 2010). Nonetheless, once people were covered by health insurance their risk of incurring catastrophic expenditures decreased significantly (Smith-Spangler et al., 2012). An important cost factor that was predominantly investigated in studies on LMICs were non-medical costs for transportation, informal healthcare or food which were found to considerably add to the experienced diabetes cost burden (Chatterjee et al., 2011; Esteghamati et al., 2009; Tharkar et al., 2010; Wang et al., 2009a,b).

In terms of the costing methodology applied in COI studies, the number of studies estimating the excess costs of diabetes increased since the Ettaro et al. (2004) review. Those studies either used regression analysis or matching to adjust for the differences between people with diabetes and those without, accounting at least for age and gender, but often also for other socioeconomic, geographic and demographic differences. Other widely used approaches to estimate direct healthcare costs from the perspective of the healthcare system or private insurance included the disease-attributable and—slightly less frequently—the attributable-fraction approach. For cost assessment in LMICs, studies often either estimated

total healthcare costs or carried out self-administered surveys. While Ettaro et al. (2004) recommended the use of disease-attributable approaches to arrive at more exact estimates of the costs of diabetes, the evidence found in this review indicates that using an incremental cost approach via matching or regression analysis could provide more accurate results, due to its ability to capture costs otherwise not directly traceable to diabetes. Nonetheless, the use of the estimation technique always hinges on the availability of appropriate data, with regression or matching analyses requiring information on people without diabetes to be used as a control group. Therefore, the estimation approach needs to be tailored to the available data.

Compared with the evidence reviewed by Ettaro et al. (2004), the field has generally advanced with respect to the analysis of costs in different ethnic and age groups. Two studies investigated differences between racial groups in the USA, showing that while ethnic minorities spend less on diabetes healthcare than Whites, this difference seems to be mainly based on differences in access to care between Whites and Blacks or Hispanics (Buescher et al., 2010; Lee et al., 2006). In terms of age, studies found an increase in healthcare costs with age as well as with, in some cases, the duration of diabetes. A recurring problem was that many studies did not distinguish diabetes types, making it difficult to exactly attribute the costs to the respective diabetes types.

To explore the reasons for the wide heterogeneity in direct cost estimates across studies, we performed a regression analysis, which indicated that an important determinant for the cost variation across countries could be the economic wealth of the country (proxied by GDP per capita), similar to what was found in a review of indirect costs of various chronic diseases (Zhao et al., 2013a), possibly due to differences in the availability and affordability of diabetes care between HICs and LMICs (Cameron et al., 2009; Cameron et al., 2011).

Further, studies on the USA seem to estimate consistently higher costs than studies on other countries, even when accounting for differences in GDP per capita. The higher direct costs of diabetes estimated for the USA are in line with the generally higher healthcare expenditures in the USA compared with countries with similar income levels, and could be the result of exceptionally high service fees (Laugesen et al., 2011) and prices paid in the USA healthcare system (Lorenzoni et al., 2014; Squires, 2012).

Because of the small sample size on which our analysis was based, these results must be interpreted with caution, and other factors could still be important. For instance, other evidence suggests that different costing approaches have a considerable effect on diabetes cost estimates (Honeycutt et al., 2009; Tunceli et al., 2010). Furthermore, the perspective taken, different data sources and populations investigated and decisions on the cost components included are likely

important in explaining within-country heterogeneity. In particular, the inclusion of diabetes complications and decisions about which complication(s) to include, as well as the extent to which costs for these diseases are attributable to diabetes, can significantly affect the results. Not all studies in the review provide extensive information about how they include complications and some do not include them at all.

Finally, the quality of the data used could have affected the cost estimates. Many studies in LMICs relied on self-reported data from small household surveys, limiting their generalizability and leading their results to be prone to recall bias. Further, these studies often identified people with diabetes via their use of healthcare institutions, which excluded a potentially important section of the population in LMICs unable to access formal care, possibly leading to an overestimation of the average diabetes-related costs.

Labour market studies

Turning to the effects of diabetes on the labour market, the existing studies showed, almost consistently, with the exception of Canada (Latif, 2009) and one study on the USA (Minor, 2013), that the employment probabilities of men were affected more adversely by the disease than those of women. However, while most studies have tried to tentatively explain these gender differences, the reasons for this have not been investigated in depth. The studies also showed that, when interpreting this research, it is important to consider whether a study has tried to account for unobservable factors or reverse causality, as otherwise the results might be misleading. Nonetheless, all studies using IV techniques used similar instruments to achieve identification, providing scope for further research using different identification strategies to explore how endogeneity might affect the results. What has been apparent is the lack of research on labour market outcomes of diabetes in LMICs, with only one study investigating the effect of diabetes on labour income in China (Liu et al., 2014). This deficit might be due to a limited availability of suitable data sources containing sufficient information to allow for a similar investigation of the topic.

The potential for rich, good-quality data sources to aid the investigation of the economic impact of diabetes can be illustrated by the several studies that used data from the Lower Rio Grande Valley in Texas. These studies demonstrate the evolution of methodology and data from the use of single equation regression models (Bastida et al., 2002a) to the use of IV methods (Brown et al., 2005b) and—finally—biometric data on blood glucose values (Brown et al., 2011). While the first two methods allowed the investigation of the general effect of diabetes on employment probabilities, the latter was able to assess the impact accord-

ing to how diabetes was managed by the patient, as proxied by the measured biomarkers. The study found that the main adverse effect was due to having diabetes regardless of how it was managed and that improvements in management only had minor positive effects. The authors concluded that investments in the prevention of diabetes would likely be more effective than improved diabetes management.

The latter study and the study by Liu et al. (2014) also show how biometric data (e.g. blood glucose values) can be used to arrive at a deeper understanding of the economic effects of diabetes. Biometric information makes it possible to investigate the impact of diabetes according to the severity of the disease and also allows for the consideration of previously undiagnosed people with diabetes, increasing the policy relevance of the research.

Comparison of COI and labour market studies: common themes and lessons learned

The results of both fields, COI and labour market studies, show a considerable adverse impact of diabetes in terms of costs to society, health systems, individuals and employers and in terms of a reduction in the productive workforce and productivity in general. Both research strands particularly indicate that the adverse effects of diabetes increase with diabetes duration as well as with the severity of the disease, judged by the high complication costs estimated in COI studies and the larger employment and income penalties for those with a longer disease duration or higher blood glucose levels.

Nonetheless, several lessons can be learned for each field from advancements in the other field. Future COI studies would, for instance, benefit from the more frequent use of biomarker data. This would allow for a more precise analysis of the costs of diabetes according to the severity of the disease and help inform researchers and policy makers about the possible economic effects of achieving certain treatment goals, e.g. a reduction in blood glucose values.

Also, and in contrast to the labour market outcomes literature, the endogeneity problem has hitherto not been addressed in any form in studies estimating direct healthcare or productivity costs, despite it being an equally important challenge in this domain. A possible bias could arise if some people developed diabetes as a result of an unobserved accident or illness, likely resulting in an overestimation of the costs. Endogeneity could also be introduced if people with diabetes became poorer as a result of the disease and consequently were not able to spend as much on their treatment as they would like to, leading to an underestimation of the true monetary cost of diabetes. Furthermore, an endogeneity bias would be introduced if diabetes was correlated with poverty so that diabetes prevalence would be

disproportionately high in subgroups with less resources and consequently less access to care. This would lead to an underestimation of the healthcare costs of diabetes. Endogeneity in COI studies has recently been addressed for the estimation of healthcare costs of obesity, suggesting that direct costs would have been underestimated, had the study not accounted for endogeneity (Cawley et al., 2012). It appears that, on the basis of the studies identified in our review, a similar—worthwhile—approach could and should be applied to the case of type 2 diabetes.

Yet the labour market studies also stand to gain from adopting certain approaches that are more common in COI studies. To date, only few labour market studies have used the incidence approach found for COI studies to follow people with diabetes over a certain time period from their diagnosis onwards, in order to further explore how the effect of diabetes on employment and productivity measures develops over time.

Some further recommendations may be derived for future COI and labour market studies on diabetes:

1. For COI studies the estimation of incremental costs—wherever possible—appears to be most suitable for diabetes, as it more accurately accounts for costs of co-morbidities and for less obviously related disease costs (Honeycutt et al., 2009; Tunceli et al., 2010). More information that can guide researchers in their choice of methods already exists and should be referred to when performing a COI study (Akobundu et al., 2006).

2. If possible, the use of convenience samples of people with diabetes visiting a healthcare institution should be avoided, particularly in LMICs, as it excludes those not able to visit a clinic for treatment due to economic reasons, leaving out a potentially important proportion of diabetes patients.

3. The interpretation of the COI results always hinges on the amount of information provided about, among others, the aim of the study, the perspective adopted and the cost components included as well as the used estimation approach. A discussion of how these choices might affect the estimates should also be part of every COI study. Researchers should therefore consult available guidance from the literature that sets out what information should ideally be included in a COI study (Larg et al., 2011) to increase the transparency and usability of their research.

4. For labour market studies more evidence from LMICs is needed. There is scope for exploring existing household datasets from LMICs that contain information on diabetes (Seuring et al., 2014). In some cases, panel data are (or may become) available, which would allow the investigation of the

effects of diabetes over time as well as to improve the degree of causal inference by controlling for unobserved heterogeneity.

5. As for labour market studies, other ways of achieving identification should be explored to reduce the reliance on IV methods using the family history of diabetes as the sole instrument. The increasing richness of information provided in recent data sets could be used to this effect, also taking into account other quasi-experimental econometric methods (Craig et al., 2012).

Limitations

A possible limitation of this review is the decision to refrain from excluding studies based on certain quality criteria, such as study design, costing methodology, sample size or reporting standards. This might have resulted in the inclusion of lower quality studies with less reliable estimates, compromising the comparability across countries, particularly between LMICs and HICs, as study designs differed considerably. On the other hand, our overarching objective was to ensure a truly globally comprehensive overview of the literature on the economic impact of diabetes, including evidence from LMICs, which, for reasons often beyond the control of the researchers, may have been of limited quality and thus would have been excluded, had we applied stringent quality benchmarks. Further, any attempt to apply a quality threshold would have faced the challenge of dealing with the absence of a formal checklist to follow in critically appraising the quality of COI studies. Rather than interpreting it as a limitation, we see the identification and synthesis of LMIC studies as a unique added value of this review, when compared to the Ettaro et al. (2004) review.

Notably, we also abstained from any language restrictions, which would have particularly excluded evidence from Spanish speaking and Eastern European countries. Taken together, these factors have resulted in a large number of included studies, allowing for an (albeit exploratory) statistical investigation of the heterogeneity in diabetes cost estimates as a complement to the narrative analysis. We therefore feel that the advantages of refraining from too stringent inclusion criteria more than outweigh the possible negative consequences of including potentially lower-quality studies.

Further, our search was limited to studies after the year 2000. While for COI studies a previous review covered the literature until 2000, this is not the case for the literature on labour market effects of diabetes and we therefore cannot exclude the possibility of having missed some relevant (if old) studies. We have checked the references of our included labour market studies for any relevant studies published before 2001. We could find only one relevant study from 1998 investigating how employment chances and family income were affected by di-

abetes in the USA, comparing samples from 1976, 1988 and 1992 and finding significant adverse effects of diabetes on employment probabilities but not on family income (Kahn, 1998). The effect for women decreased somewhat between 1976 and 1992, while the effect increased for men. The study did not account for the possible endogeneity of diabetes nor selection bias when estimating the effects on income.

Conclusion

This review has provided an updated and considerably expanded picture of the literature on the global economic impact of type 2 diabetes. The results show a considerable impact of diabetes in terms of costs to society, health systems, individuals and employers and in terms of a reduction in the productive workforce and productivity in general. Studies on the costs of diabetes now provide evidence from HICs as well as LMICs, using a variety of study designs to estimate the costs of diabetes. The evidence indicates a particularly strong and direct economic impact of type 2 diabetes on people's livelihoods in lower-income settings. Studies on labour market outcomes so far have been confined, almost exclusively, to HICs, leaving space for further studies in LMICs to provide additional evidence of the effect of diabetes in these countries. An issue not yet covered in diabetes COI studies—in striking contrast to labour market outcome studies—has been the possible bias introduced by endogeneity, providing an opportunity for advancing research in this area.

3 The impact of diabetes on employment in Mexico

Pre-amble

The systematic review in Chapter 2 identified a paucity of studies on the labour market impact of diabetes in developing countries. Further, even studies on high-income countries (HICs) did not provide much information regarding the heterogeneity of effects across different socioeconomic subgroups. There was no evidence on how diabetes may affect those in the formal compared to the informal labour market or across the wealth distribution. Further, it was unclear what the effects were for people unaware of their disease.

This study will use cross-sectional data from a large household survey in Mexico, assessing the impact of diabetes on employment probabilities. An instrumental variable (IV) strategy inspired by preceding studies from HICs is used to account for the potential endogeneity of diabetes due to unobserved heterogeneity. Especially personal characteristics such as ambition and family background could affect both the probability to develop diabetes, in particular type 2 diabetes, and the probability of being employed. The aim is to investigate if diabetes has a causal effect on employment probabilities and to provide evidence for the subgroup of those in the informal labour market and the relatively poor, populations of particular relevance in middle-income countries (MICs).

Abstract

This study explores the impact of diabetes on employment in Mexico using data from the Mexican Family Life Survey (MxFLS) (2005), taking into account the possible endogeneity of diabetes via an instrumental variable estimation strategy. We find that diabetes significantly decreases employment probabilities for men by about 10 percentage points ($p<0.01$) and somewhat less so for women—4.5 percentage points ($p<0.1$)—without any indication of diabetes being endogenous. Further analysis shows that diabetes mainly affects the employment probabilities of men and women above the age of 44 and also has stronger effects on the poor than on the rich, particularly for men. We also find some indication for more adverse effects of diabetes on those in the large informal labour market compared to those in formal employment. Our results highlight—for the first time—the detrimental employment impact of diabetes in a developing country.

Introduction

Diabetes, similar to other conditions that have been coined "diseases of affluence", has traditionally been seen as mostly a problem of the developed, more affluent countries. Only in recent years the awareness has been growing of the sheer size of the problem in health terms (Hu, 2011; Yach et al., 2006). Mexico is one example of a middle-income country that has seen diabetes rates increase sharply over the last years, from about 7.5% in 2000 (Barquera et al., 2013) to 12.6% in 2013 (International Diabetes Federation, 2014). The high prevalence of diabetes in Mexico reflects an epidemiological transition from a disease pattern previously characterized by high mortality and infectious diseases to low-mortality rates and non-communicable diseases (NCDs) affecting predominantly adults (Stevens et al., 2008). This transition has likely been reinforced by nutritional changes away from a traditional diet towards an energy dense, but nutritionally poor diet with an increasing amount of processed foods and sugars (Barquera et al., 2008; Basu et al., 2013; Rivera et al., 2004), a reduction in physical activity, as well as what appears to be a particular genetic predisposition of many Mexicans to develop type 2 diabetes (Williams et al., 2013). While many of the high-income countries may be in a position to cope resource-wise with the healthcare consequences of diabetes, this will be less so the case for Mexico and other low- and middle-income countries (LMICs). The most recent cost-of-illness estimates put the costs of diabetes to the Mexican society at more than US$778 million in 2010, with a large part of these costs being paid out-of-pocket (Arredondo et al., 2011a). While the above includes some estimate of indirect costs, meant to capture the cost burden attributable to foregone productivity resulting from

diabetes, there exists no rigorous, econometric assessment of the effect of diabetes on employment probabilities for Mexico, as the research has thus far focused on high-income countries (Bastida et al., 2002a; Brown et al., 2005b; Latif, 2009; Lin, 2011; Minor, 2011; Vijan et al., 2004; Zhang et al., 2009).

There are several reasons to expect a significant adverse effect of diabetes on employment probabilities in Mexico and that this effect might be stronger than in high-income countries. In Mexico type 2 diabetes is increasingly affecting people in their productive age, raising the possibility that a larger share of people with diabetes will have to cope with debilitating complications already relatively early in life (Barquera et al., 2013; Villalpando et al., 2010). Further, only a minority of Mexicans appears to successfully manage their diabetes condition, with as much as 70% of the people with diabetes having poor control over their disease (Villalpando et al., 2010). In addition, many Mexicans are working in the large informal economy[1], possibly limiting their access to quality healthcare and hence to appropriate treatment options. All these factors are likely to both increase the risk of developing debilitating diabetes complications as well as to reduce productivity as a result. Against this background, the aim of this study is to investigate how diabetes affects employment probabilities in a middle-income country such as Mexico. To the best of our knowledge this is the first such paper on Mexico and indeed on any LMIC. We also investigate if the impact of diabetes on employment probabilities differs across age groups and—again for the first time in this field—by wealth, as well as between those formally and informally employed.

The majority of the more recent studies on the labour market impact of diabetes tried to account for the possible endogeneity of diabetes using family history of diabetes as an instrument. Endogeneity might arise due to reverse causality: employment status and its effect on a person's lifestyle may also influence the odds of developing diabetes. A job with long office working hours might push a person's diet or exercise pattern towards a more unhealthy and sedentary lifestyle due to reduced leisure time, increasing the person's risk for diabetes. In addition, unobserved factors, such as personal traits, could simultaneously influence a person's employment as well as his or her diabetes status and introduce an omitted variable bias. A less ambitious person could be less productive in a job, increasing the risk of being laid off, and he or she could simultaneously have only modest, if any, exercise goals or healthy eating habits, thereby increasing the chances of developing diabetes.

Brown et al. (2005b) estimated the impact of the disease on employment in 1996–1997 in an older population of Mexican Americans in the USA close to the

[1]In 2005 around 58% of the working population in Mexico were employed in the informal sector (Aguila et al., 2011).

Mexican border, using an IV strategy. They found diabetes to be endogenous for women but not for men. The results of the IV estimation suggested no significant effect on women which, compared to the adverse effect found in the univariate probit model, indicated an overestimation of the effect for women when endogeneity was not accounted for. For men, the univariate probit estimates showed a significant adverse effect of about 7 percentage points. Latif (2009) estimated the effect of the disease on employment probabilities in Canada in 1998. Contrary to Brown et al. (2005b), he found diabetes to be exogenous for females and endogenous for males; taking this into account he obtained a significant negative impact on the employment probabilities for women, but not for men. Because the simple probit model showed a significant negative effect for males, Latif (2009) concluded that not accounting for endogeneity resulted in an overestimation of the effect on male employment probabilities. Minor (2011) investigated the effect of diabetes on female employment, among other outcomes, in the USA in 2006. This particular study differed from earlier work in that it not only analysed the effects of diabetes in general, but also of type 1 and type 2 diabetes separately. The study found diabetes to be endogenous and underestimated if exogeneity was assumed. In the IV estimates, type 2 diabetes had a significant negative effect on female employment probabilities. For Taiwan, Lin (2011) found diabetes to be endogenous, with the IV results showing significant changes in the employment effect of diabetes. The impact was found to be significantly negative for men in the IV model indicating an underestimation in the standard probit model, where the diabetes coefficient was also significant but much smaller in size. For women, no significant effect was found in the IV estimation after the probit model had indicated a significant and negative impact of diabetes.

Accordingly, at least in some cases, there seems to be the risk of biased estimates of the impact of diabetes on employment, when exogeneity is assumed, with an a priori ambiguous bias. Hence, our decision in this study to also assess if diabetes is endogenous and how precisely taking account of endogeneity might affect the estimates. In order to account for this possible endogeneity we use data from the second wave of the Mexican Family Life Survey (MxFLS) from 2005, which not only provides information on people's diabetes status and socioeconomic background, but also on parental diabetes, enabling us to construct an instrumental variable similar to what has been used in the previous literature on high-income countries.[2] The data also allows the extension of the analysis to test if the inclusion of information on parental education as an additional control variable affects the IV parameter estimates.

[2]Studies that have used the family history of diabetes as an instrument for diabetes are Brown et al. (2005b) for a Mexican-American community, Latif (2009) for Canada, Minor (2011) for females in the USA and Lin (2011) for Taiwan.

Methodology

Dataset and descriptive statistics

The dataset used for the empirical analysis is the Mexican Family Life Survey (MxFLS). It is a nationally representative household survey which was conducted in 2002 and 2005. We use data from the second wave in 2005, which includes almost 40,000 individuals. Interviews were conducted with all household members aged 15+, and information on a wide range of social, demographic, economic and health related topics was collected (Rubalcava et al., 2008). While there are more recent datasets available on Mexico, none of these provide as extensive information on parental characteristics as does the MxFLS which includes information on parental diabetes and education status, even if parents were not alive any more or were living in a non-surveyed household at the time of the survey. Diabetes is self-reported and 3.7% of males and 5.1% of females report a diagnosis by a doctor.[3] Unfortunately we cannot—with the data at hand—distinguish between the different types of diabetes. It can be assumed, however, that about 90% of the reported diagnoses are due to type 2 diabetes, which is by far the most common type of diabetes (Sicree et al., 2011). The sub-sample used for analysis is limited to the age group of 15 to 64 years, which represents the majority of the working population. To allow for heterogeneity in the coefficients across gender, the sample has been split to estimate the male and female groups separately.

The descriptive statistics presented in Table 7 suggest that the groups of respondents with and without diabetes differ significantly in various aspects. Both males and females with diabetes have a lower employment rate than their counterparts. This would suggest that diabetes has a negative impact on the employment probabilities of both males and females with diabetes. However, since the groups with diabetes are also significantly older and differ in terms of education, this may be a spurious relationship. As a result, only a multivariate analysis will provide more reliable information on how diabetes truly affects employment probabilities.

[3] This is well below the estimated prevalence rate for 2013 of almost 12%. This is likely due to the fact that, according to the International Diabetes Federation (IDF), more than half of the people with diabetes in Mexico are undiagnosed and consequently did not report it (International Diabetes Federation, 2014). Further, the sample in the survey at hand is restricted to people between the age of 15 to 64, which does not match exactly with the population the IDF used for the diabetes prevalence estimates (20 – 79). Hence, our used sample includes a greater share of young people with a very low diabetes prevalence and excludes people above 64 years of age, which likely have a higher than average prevalence rate. Taken together, this—as well as a further increase in prevalence since 2005—should explain the difference between the diabetes prevalence in our sample and the one estimated by the IDF.

Table 7: Summary statistics for males and females with and without diabetes

	Males			Females		
	Mean with diabetes	Mean without diabetes	p (t-test)	Mean with diabetes	Mean without diabetes	p (t-test)
Employed	0.714	0.804	0.000	0.229	0.313	0.000
Age	50.945	35.016	0.000	48.955	34.717	0.000
Age 15–24	0.008	0.294	0.000	0.036	0.282	0.000
Age 25–34	0.043	0.232	0.000	0.076	0.250	0.000
Age 35–44	0.161	0.196	0.162	0.180	0.221	0.042
Age 45–54	0.392	0.166	0.000	0.366	0.159	0.000
Age 55–64	0.396	0.111	0.000	0.342	0.089	0.000
Rural	0.337	0.399	0.047	0.391	0.399	0.723
Small city	0.082	0.126	0.038	0.144	0.123	0.204
City	0.145	0.102	0.028	0.103	0.098	0.737
Big city	0.435	0.372	0.042	0.362	0.379	0.475
Southsoutheast	0.208	0.203	0.864	0.184	0.206	0.270
Central	0.243	0.184	0.017	0.231	0.195	0.062
Westcentral	0.173	0.213	0.124	0.191	0.210	0.343
Northeastcentral	0.196	0.177	0.446	0.209	0.186	0.236
Northwestcentral	0.180	0.223	0.112	0.184	0.202	0.355
No education	0.090	0.062	0.070	0.151	0.081	0.000
Primary	0.518	0.352	0.000	0.607	0.368	0.000
Secondary	0.231	0.308	0.009	0.171	0.314	0.000
High school	0.059	0.158	0.000	0.043	0.138	0.000
College or university	0.102	0.120	0.379	0.029	0.098	0.000
Indigenous	0.137	0.121	0.448	0.133	0.118	0.341
Married	0.812	0.535	0.000	0.663	0.539	0.000
Children (under 15)	1.118	1.510	0.000	1.207	1.600	0.000
Wealth	0.179	−0.010	0.003	0.004	−0.003	0.885
Diabetes father	0.180	0.071	0.000	0.146	0.079	0.000
Diabetes mother	0.251	0.107	0.000	0.236	0.113	0.000
Education parents	0.596	0.697	0.001	0.528	0.699	0.000
Formal employment	0.286	0.306	0.508	0.083	0.140	0.001
Informal employment	0.529	0.560	0.342	0.191	0.220	0.155
N	255	6031		445	7798	

Econometric specification

We first estimate a probit model with the following specification

$$Employed_i = \beta_0 + \beta_1 Diabetes_i + \beta_2 X_i + u_i \quad (1)$$

where diabetes is assumed to be exogenous. $Employed_i$ takes the value of 1 if person i is employed and 0 if unemployed. Employment status is defined as having worked or carried out an activity that helped with the household expenses for at least ten hours over the last week. This explicitly includes those employed informally, for instance people working in a family business.

$Diabetes_i$ denotes the main independent variable of interest, taking the value of 1 if individual i has reported a diagnosis of diabetes and 0 otherwise.

X_i contains various control variables. Because no information on job history is available in the data to adequately account for work experience, we need to rely on the combination of age and education to proxy for work experience (Aaronson, 2010). The effect of age is captured through dummy variables for age intervals. Education is taken into account by dummy variables indicating if the highest level of schooling attained was either primary school, secondary school, high school, university or some other form of higher education with no education serving as the reference category, to control for the impact of education on employment and to account for the relationship between diabetes and education (Agardh et al., 2011).

Since Mexico is a large and diverse country with regional socioeconomic differences we also include dummies for five different Mexican regions[4]. Apart from the more obvious effects economic differences between regions can have on employment probabilities and diabetes through their impact on employment opportunities and lifestyles, the dummies should also account for less obvious effects that macroeconomic problems, such as a high unemployment rate, could have on employment probabilities and diabetes by affecting psychological well-being and sleeping patterns (Antillón et al., 2014). Because differences in economic opportunities and lifestyles should also be expected between rural and urban areas, three dummy variables are included to capture the effects these factors might have on employment probabilities and diabetes, with living in a rural area being the reference category[5] (Villalpando et al., 2010). Further, to control for labour

[4]The region variables have been constructed after recommendations on the MxFLS-Homepage. South-southeastern Mexico: Oaxaca, Veracruz, Yucatan; Central Mexico: Federal District of Mexico, State of Mexico, Morelos, Puebla; Central northeast Mexico: Coahuila, Durango, Nuevo Leon; Central western Mexico: Guanajuato, Jalisco, Michoacan; Northwest Mexico: Baja California Sur, Sinaloa, Sonora.

[5]Rural: $<$ 2,500 inhabitants; Small city: 2,500 to 15,000 inhabitants; City: 15,000 to 100,000 inhabitants; Big city: $>$ 100,000 inhabitants.

market discrimination and possible differences in genetic susceptibility to diabetes of indigenous populations (Yu et al., 2007), a dummy for being a member of an indigenous group is included. We also account for the marital status to control for the impact of marriage on employment probabilities and lifestyle habits. Further a variable capturing the number of children residing in the household below the age of 15 is included, to control for their impact on employment probabilities and for the effect of childbearing and related gestational diabetes on the probabilities of women to develop type 2 diabetes (Bellamy et al., 2009).

To account for the effect that household wealth might have on diabetes and employment probabilities, we use the well established method of principal component analysis of multiple indicators of household assets and housing conditions to create an indicator for household wealth (Filmer et al., 2001). Our composite wealth index consists of owning a vehicle, owning a house or other real estate, owning another house, owning a washing machine, dryer, stove, refrigerator or furniture, owning any electric appliances, owning any domestic appliances, owning a bicycle and owning farm animals. It further accounts for the physical condition of the house, proxied by the floor material of the house, and the type of water access.

The error term is denoted as u_i. We do not control for the general health status and other diabetes related chronic diseases as they are likely determined by diabetes itself and, hence, could bias the estimates and compromise a causal interpretation of the effect of diabetes on employment (Angrist et al., 2009).

As diabetes could be endogenous, the probit model might deliver biased estimates. Therefore we employ an IV strategy, using a bivariate probit model to estimate the following two equations simultaneously:

$$Diabetes_i = \delta_0 + \delta_1 X_i + \delta_2 diabetesmother_i + \delta_3 diabetesfather_i + \eta_i \quad (2)$$

$$Employed_i = \beta_0 + \beta_1 Diabetes_i + \beta_2 X_i + u_i \quad (3)$$

In equation. 2, $Diabetes_i$ is a dummy variable and is modelled as a function of the same socioeconomic and demographic factors X_i as in equation 1 and of the instrumental dummy variables $diabetesmother_i$ and $diabetesfather_i$, indicating if the father or the mother had been diagnosed with diabetes. The error term is denoted as η_i. equation 3 is identical to the probit specification (equation 1) and estimates the effect of diabetes on employment, now taking into account the possible endogeneity of diabetes. Diabetes is exogenous if the error terms of both equations are independent of each other ($Cov(u_i \eta_i) = 0$). Endogeneity is tested using a likelihood ratio test based on the idea that if $Cov(u_i \eta_i) = 0$, the log-

likelihood for the bivariate probit will be equal to the sum of the log-likelihoods from the two univariate probit models (Knapp et al., 1998). If u_i and η_i are correlated, the estimation of equation 1 using a probit model will not provide consistent estimates of the impact of diabetes on employment. In this case the simultaneous estimation of both equations using the bivariate probit should be preferred. For the estimation of the bivariate probit model it is assumed that u_i and η_i are distributed randomly and bivariate normal. To test the assumption of normality, we use Murphey's goodness-of-fit score test with the null-hypothesis of bivariate normally distributed errors, as suggested by Chiburis et al. (2012).[6]

We choose the bivariate probit model over the linear IV model to account for endogeneity, as there is evidence that it performs better if the sample is relatively small (<5,000) and—more important in our case—when treatment probabilities are low. In such cases the linear IV can produce uninformative estimates while the bivariate probit model has been shown to provide much more reasonable results (Chiburis et al., 2012). Because only 4% of males and 5.4% of females report a diagnosis of diabetes, treatment probabilities are indeed low in the given case, providing good justification for the use of the bivariate probit model.

In order to fulfil the conditions of a valid instrument, parental diabetes needs to impact the diabetes risk of the offspring while at the same time being unrelated to the offspring's employment chances. It has been shown that there is a strong hereditary component of type 2 diabetes which predisposes the offspring of people with diabetes to develop the condition as well (Herder et al., 2011; The Interact Consortium, 2013). This is supported by the notion that genes seem to play a crucial role, besides the recent epidemiological transition and the migration from rural to urban areas, in explaining Mexico's high diabetes prevalence according to a recent study by Williams et al. (2013). The authors identified a specific gene particularly prevalent in Mexican and other Latin American populations with native American ancestry, which is associated with a 20% increase in the risk of developing type 2 diabetes. Furthermore, research has shown that parental lifestyle factors, socioeconomic background as well as parental body mass index (BMI) can explain but a very small fraction of the increased risk of type 2 diabetes in the offspring, which is why we assume that the increased risk is mainly due to genetic factors unrelated to lifestyle (Herder et al., 2011; The Interact Consortium, 2013). This is supported by Hemminki et al. (2010), who find that adoptees whose biological parents had type 2 diabetes, had an increased risk of developing type 2 diabetes even though they were living in a different household, while if their adopted parents had the disease, they had no elevated

[6]Murphey's score test "...embeds the bivariate normal distribution within a larger family of distributions by adding more parameters to the model and checks whether the additional parameters are all zeros using the score for the additional parameters at the bivariate probit estimate." (Chiburis et al., 2012, p. 19).

risk.

Nonetheless, there might still be the chance that parental diabetes decreases the offspring's employment probabilities. The additional financial burden of diabetes or an early death due to diabetes could have prevented the parents from investing in their children's education the way they would have liked to or it could have led to the child dropping out of school in order to support the family. However, controlling for education should account for these effects if they exist. Therefore parental diabetes should be a valid instrument which predicts diabetes while not affecting employment probabilities through other unobserved pathways. To further improve instrument validity we also account for the possibility that parental education is simultaneously correlated with the parental diabetes status as well as their children's employment chances, by including a dummy variable indicating if any of the parents had attained more than primary education.

A possible limitation of using parental diabetes as our instrument is that it might directly affect the offspring's employment decision through other pathways than education. Conceivably, diabetes might deteriorate parental health in such a way that the offspring has or had to give up its own employment in order to care for its parents or is forced to take up work to financially provide for the parents. With the data at hand we are unable to account for this, but if this effect exists it should be picked up by the overidentification test.

We also estimate the linear IV model as it is consistent even under non-normality (Angrist et al., 2009). The linear IV model takes the following form of a first (equation 4) and a second stage (equation 5).

$$Diabetes_i = \pi_0 + \pi_1 X_i + \pi_2 diabetesmother_i + \pi_3 diabetesfather_i + \eta_i \qquad (4)$$

$$Employed_i = \beta_0 + \beta_1 Diabetes_i + \beta_2 X_i + u_i \qquad (5)$$

In the second stage, the potentially endogenous actual diabetes values are replaced with the predicted values from the first stage. The covariates are the same as in the bivariate probit case described in equation 2 and equation 3. In the linear IV model the Hausman test is used to identify endogeneity. Validity of the instruments is tested using first stage diagnostics of the linear IV model, as similar tests are not available for the bivariate probit model. Average marginal effects are presented for the probit and bivariate probit models.

Results

This section presents the estimation results using 1) a probit model model that assumes diabetes to be exogenous and 2) IV models with parental diabetes as an instrument for diabetes, to determine if diabetes is endogenous or if instead the results from the probit model can be used.

Probit results

Table 8 indicates that the effect of diabetes is negative for both sexes. For males, it reduces the probability of being employed by 10 percentage points ($p<0.01$).

For females, the effect is also negative but smaller, and shows a reduction in employment probabilities of about 4.5 percentage points ($p<0.1$).

The other covariates largely show the expected relationships. Employability increases with age and is highest for the 35–44 years age group. Especially for women, living in a more urban environment increases employment probabilities compared to women living in rural areas. Also, women seem to benefit substantially from higher education in terms of employment probabilities. For men the effects of education are also positive, though, not as marked as for women. Perhaps surprisingly, being part of an indigenous population does not affect employment probabilities, neither for males or females.

The probit results suggest a significant negative effect of diabetes on the employment probabilities of males and likely also females in Mexico. In light of the concern that diabetes could be endogenous the following section presents the results of the IV estimations.

IV results

Using the bivariate probit model, the diabetes coefficient for males increases in size and remains negative whereas for females it decreases but also remains negative. However, standard errors increase in both models and the results turn insignificant, suggesting considerable loss of efficiency (see Table 9). The likelihood-ratio test does not reject the null hypothesis of no correlation between the disturbance terms of equation 2 and equation 3 for males and females, suggesting exogeneity of diabetes. The test for normality of the error term does not reject the null hypothesis of normality for the male and the female model, increasing our confidence in the estimates. Nonetheless we also consider the results of the linear IV model (see Table 10 displaying the main results and Table A5 in the appendix presenting the complete first and second stage estimates): the test statistics indicate sufficiently strong and valid instruments, as shown by the Kleibergen-Paap Wald F statistic for weak instruments of 20.48 for men and 27.71 for women,

Table 8: Impact of diabetes on employment probabilities (probit)

	(1) Males		(2) Females	
Age 25–34	0.124***	(.011)	0.121***	(.017)
Age 35–44	0.133***	(.012)	0.232***	(.018)
Age 45–54	0.085***	(.014)	0.170***	(.022)
Age 55–64	−.034	(.020)	0.039	(.026)
Small city	−.013	(.017)	0.043**	(.020)
City	−.036*	(.019)	0.042**	(.021)
Big city	0.029**	(.013)	0.101***	(.014)
Central	0.027	(.015)	−.032*	(.018)
Westcentral	0.020	(.015)	−.008	(.018)
Northeastcentral	0.003	(.016)	−.053***	(.017)
Northwestcentral	−.037**	(.016)	−.100***	(.016)
Primary	0.056***	(.020)	−.006	(.022)
Secondary	0.051**	(.021)	0.058**	(.025)
High school	0.040*	(.023)	0.126***	(.029)
College or university	0.047**	(.023)	0.297***	(.033)
Indigenous	0.005	(.016)	−.005	(.020)
Married	0.092***	(.012)	−.231***	(.012)
Children (under 15)	0.010**	(.004)	−.018***	(.004)
Wealth	0.002	(.006)	0.037***	(.007)
Education parents	−.007	(.013)	0.000	(.013)
Diabetes	−.100***	(.029)	−.045*	(.023)
Log likelihood	−2897.807		−4508.573	
N	6286		8243	

Notes Average marginal effects; robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Impact of diabetes on employment probabilities (bivariate probit)

	(1) Males		(2) Females	
Age 25–34	0.125***	(.012)	0.109***	(.015)
Age 35–44	0.134***	(.012)	0.207***	(.016)
Age 45–54	0.089***	(.016)	0.149***	(.021)
Age 55–64	−.025	(.025)	0.032	(.029)
Small city	−.014	(.017)	0.039**	(.018)
City	−.035**	(.018)	0.038**	(.019)
Big city	0.030**	(.013)	0.093***	(.013)
Central	0.027	(.018)	−.030*	(.015)
Westcentral	0.019	(.018)	−.007	(.016)
Northeastcentral	0.002	(.018)	−.049***	(.017)
Northwestcentral	−.038**	(.017)	−.091***	(.015)
Primary	0.057***	(.020)	−.006	(.021)
Secondary	0.052**	(.023)	0.052**	(.022)
High school	0.040	(.025)	0.113***	(.027)
College or university	0.046*	(.025)	0.273***	(.032)
Indigenous	0.006	(.017)	−.005	(.016)
Married	0.093***	(.012)	−.215***	(.011)
Children (under 15)	0.010**	(.004)	−.016***	(.004)
Wealth	0.002	(.006)	0.033***	(.007)
Parental education	−.006	(.013)	0.000	(.012)
Diabetes	−.185	(.143)	−.021	(.108)
Instruments				
Diabetes father	0.048***	(.011)	0.041***	(.010)
Diabetes mother	0.037***	(.008)	0.054***	(.008)
Log likelihood	−3737.766		−5939.588	
Score goodness-of-fit				
(H0=normality of errors)	12.32		8.85	
p value	0.196		0.451	
Endogeneity				
(H0: Diabetes exogenous)	0.443		0.039	
p value	0.506		0.844	
N	6286		8243	

Notes Average marginal effects; robust standard errors in parentheses. The presented coefficients and standard errors for the instruments result from the estimation of the model specified in equation 2, indicating the effect of parental diabetes on a person's diabetes risk. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Impact of diabetes on employment probabilities (linear IV)

	Males	Females
Diabetes	0.098	0.239
	(.215)	(.214)
R2	0.067	0.120
F stat (H0: weak instruments)	20.483	27.706
Sargan test (H0: valid instruments)	0.862	0.295
p value	0.353	0.587
Endogeneity (H0: Diabetes exogenous)	0.864	1.796
p value	0.353	0.180
N	6286	8243

Notes Robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father. Other control variables: age, region, urban, education, indigenous, marital status, children, wealth, parental education. Critical values for weak identification test F statistic: 10% maximal IV size 19.93, 15% maximal IV size 11.59, 20% maximal IV size 8.75, 25% maximal IV size 7.25. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

being above the critical value of 19.93 for 10% IV size and well above the rule of thumb of 10 for weak identification not to be considered a problem (Baum et al., 2007; Staiger et al., 1997). The Sargan test does not reject the null hypothesis of instruments uncorrelated with the error term and instruments correctly excluded from the estimated equation. The coefficients of the linear IV model are very different from the bivariate probit model, turning positive for males and females, but also very imprecise as indicated by the large standard errors. As mentioned before, Chiburis et al. (2012) show that the estimates of the linear IV model are likely to be imprecise when low treatment probabilities exist and can differ substantially from the bivariate probit model, which seems to be the case here.[7] Since the linear IV models fail to reject exogeneity of diabetes as well, we are confident that the standard probit model provides unbiased and efficient estimates of the effect of diabetes on employment chances in Mexico and should therefore be used for inference.

The next section investigates the effects of diabetes for two different age groups, 15–44 and 45–64, to explore whether, and if so, how the effect of diabetes on employment probabilities differs between older and younger people. There might be reason to believe that diabetes has a more adverse effect in older age groups, when those suffering from diabetes are likely to have accumulated more years lived with diabetes, and hence are more likely to develop complications.

Differences by age groups

When divided into an older and younger age group using the cut-off point of 45 years, the negative effect of diabetes is mainly found in the older age group, for males and females alike (see Table 11), where 12.5% report having diabetes, compared to only 1.7% in the younger age group. The probability of being employed is reduced by 11 percentage points for men between 45 and 64 years at the 1% significance level, while there is no significant effect on younger men. For women, the employment probability is reduced by about 6 percentage points, with the effect being significant at the 5% level. Similar to men, there is no effect of diabetes on younger women. To investigate in more detail for which age group the effect is strongest, we run separate regressions for both age groups above 44 years. The results (Table A6 in the appendix) show that for men the strongest effect appears in the oldest age group (i.e. 55–64 years), where employment probabilities are reduced by almost 13 percentage points. For females, a significant effect is

[7] It could also be the case that the difference in estimates is due to the fact that while the bivariate probit model estimates the average treatment effect of the variable of interest for the whole sample, the linear IV model estimates the local average treatment effect, which estimates the effect of diabetes on employment only for those that have diabetes and whose parents have or have had diabetes as well. Therefore, the estimates of both models can be different (Angrist et al., 2009; Chiburis et al., 2012).

Table 11: Impact of diabetes on employment probabilities by age group (probit)

	15-44		45-64	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	−.009	−.004	−.110***	−.057**
	(.062)	(.042)	(.034)	(.025)
Log likelihood	−1987.285	−3354.003	−925.409	−1167.491
N	4415	5997	1871	2246

Notes Average marginal effects; robust standard errors in parentheses. For the younger age group, the model contains the age categories 25–34 and 35–44 with 15–24 as the reference category. For the older age group, the model contains the age category 55–64 with 45–54 as the reference category. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

found solely for those between 45 and 54 years, where employment probabilities are reduced by 7.6 percentage points. Hence, there appear to be relevant differences between males and females in the age at which the biggest adverse effect of diabetes on employment probabilities occurs.

The use of IV methods in the age stratified samples is compromised due to a reduction in instrument power, sample size and particularly treatment probabilities. Especially for the younger age group, where treatment probabilities are close to zero, a meaningful interpretation of the IV results is difficult. Further, because no endogeneity was found in the pooled samples for males and females, we would not expect endogeneity of diabetes in the age stratified samples. We nonetheless test for the possibility of diabetes being endogenous using the bivariate probit model and an approach suggested by Lewbel (2012), to improve instrument strength (see Table A7 and Table A8 in the appendix).

Differences by wealth

To explore the heterogeneity of the effect of diabetes on employment across different levels of wealth, we divide the sample into two wealth groups at the 50^{th} percentile of our constructed wealth index.

We run separate regressions for both groups stratified by gender, finding the strongest negative effect for less wealthy males, where employment probabilities are reduced by 15 percentage points, and a smaller and less significant effect for less wealthy females (see Table 12). Whereas the coefficients for wealthier males and females have a negative sign, they are not significant at the 10% significance level. This indicates that mainly the less wealthy experience an adverse effect from diabetes. To further explore this, we stratified the sample into wealth quartiles (see Table A9 in the appendix), finding that significant adverse effects for males appear in the first and second wealth quartile, where employment probabilities are reduced by about 14 percentage points. For females a highly significant and strong effect is only found in the poorest quartile, where employment chances are reduced by 10 percentage points. Together these results indicate that the impact of diabetes on employment probabilities varies with wealth, with men and women being more affected when being in the lower wealth quartiles.

To consider the possible endogeneity of diabetes in the upper and lower wealth half, we again present the results of the IV models. The stratification into wealth groups significantly reduces instrument power as well as sample size. For none of the wealth groups the bivariate probit model indicates endogeneity (see Table A10 in the appendix). This does not change even when using the Lewbel approach to increase instrument strength and we therefore rely on the probit results for inference.

Table 12: Impact of diabetes on employment probabilities by wealth group (probit)

	Poor		Rich	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	$-.150^{***}$	$-.047^{*}$	$-.060$	$-.038$
	(.047)	(.027)	(.038)	(.035)
Log likelihood	−1459.235	−2040.517	−1408.746	−2421.910
N	3140	4091	3106	4117

Notes Average marginal effects; robust standard errors in parentheses. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Differences by employment type

To investigate the effect of diabetes on the employment probabilities in the formal and informal labour market, respectively, we estimate separate models with being employed in the formal and informal sector as the respective dependent variables. We define formal employment on the basis of having a written labour contract. Informal employment is defined as working without a written contract, being self-employed or working in semi-subsistence agriculture.

For this investigation we use two restricted samples: for the estimation of the effect of diabetes on informal employment we exclude those currently in formal employment and for the effect of diabetes on formal employment we exclude those in informal employment from our sample. We further assume that those who have worked previously and are currently unemployed are looking for employment in the same sector, i.e. if they were previously employed in the informal (formal) labour market they are again looking for an informal (formal) employment. We therefore exclude those previously working in the informal (formal) labour market from our estimation of the effect of diabetes on employment in the formal (informal) labour market. The respective sample thus only contains those currently working in the informal (formal) labour market, those previously employed in the informal (formal) labour market and those that have never worked before. Using this assumption allows the use of a normal probit model and the investigation of a possible endogeneity bias using IV techniques.

Admittedly, the assumption that the currently unemployed look for work in the same labour market they had previously worked in is quite strong and is likely not true for everybody. We therefore additionally estimate a multinomial logit model which is most useful if the decision to work is not binary but there are more than two choices, such as the choice of being either unemployed, employed in the informal or employed in the formal labour market (Wooldridge, 2002). Being unemployed is used as the reference category.

All estimated models (see Table 13 and Table A12 in the appendix), regardless of the estimation approach, indicate that diabetes significantly reduces the chances of being in informal employment, while it has no effect on formal employment.[8] This applies to both males and females. This indicates that people with diabetes are less likely to be working in the informal labour market relative to being unemployed, while there is no difference for those working in the formal labour market. We further find no indication of endogeneity (see Tables A13 and

[8]Please note, however, that the coefficients of the multinomial logit and the probit model cannot be directly compared as they are based on different assumptions. The former takes into account that a person can choose from more than two employment outcomes (i.e. being unemployed, being formally employed or being informally employed), while the latter only allows for a binary outcome without considering any other options (e.g. being unemployed or informally employed without considering the possibility of formal employment).

Table 13: Impact of diabetes on employment probabilities by employment status (probit)

	Males		Females	
	(1) Informal	(2) Formal	(3) Informal	(4) Formal
Diabetes	−.063**	−.041	−.051**	0.019
	(.031)	(.043)	(.022)	(.022)
Log likelihood	−1780.023	−1021.771	−3818.588	−1859.048
N	4604	2204	6983	5652

Notes Average marginal effects; robust standard errors in parentheses. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A14 in the Appendix). Overall, there seem to be strong differences in terms of the impact of diabetes on people in formal and informal employment, with diabetes having a stronger negative effect for those without a written contract.

Conclusion

The contribution of this paper has been to analyse—for the first time for a LMIC—the impact of diabetes on employment in Mexico, taking into account the potential endogeneity in the relationship between diabetes and employment probabilities. The presented results add to the growing literature on the adverse economic effects of diabetes. They indicate that having diabetes substantially reduces the chances to work for men and likely also for women. Hence, diabetes may contribute to a reduction in the pool of the productive workforce available to the Mexican economy.

We have also shown that diabetes reduces employment probabilities particularly in older people, likely because in this age group people are more common to already have developed diabetes-related complications which reduce their productivity and eventually force them into unemployment. Further, particularly for men the effects of diabetes on employment chances seem to be particularly strong when they belong to the poorer half of the population. While there might be some self-selection into the poorer group by those who lost their job due to diabetes and as a result descended into the lower wealth group, this finding is indicative of potentially substantial adverse equity impacts. This is also in line with our finding that diabetes reduces employment probabilities particularly for the informally employed, whereas those in formal employment seem to be less affected. Nonetheless, in order to establish causality more research in this area will be needed.

While in parts of the earlier literature diabetes was found to be exogenous only for either males or females (Brown et al., 2005b; Latif, 2009), our study found diabetes to be exogenous using the samples stratified into males and females, allowing the use of the more efficient probit model to arrive at a consistent estimate of the effect of diabetes on employment probabilities. Further, we found no endogeneity of diabetes for the sample comprised of the age group above the age of 44, for the samples stratified into an upper and lower wealth half and for the samples stratified by employment type. For the younger age group, the bivariate probit model only indicated exogeneity of diabetes for males, while for females diabetes was shown to be endogenous and having a significant positive effect of diabetes on employment. This result is rather counter-intuitive because there is no obvious reason why diabetes should increase employment probabilities. Because all samples stratified into age, wealth and employment groups suffered from

reduced instrument strength which could cause biased IV estimates, we used a method proposed by Lewbel (2012) to create additional instruments and increase instrument power. Using this method we no longer found a significant positive effect of diabetes on female employment probabilities in the younger age group and could not reject the assumption of exogeneity of diabetes in this sample. Also, for all other wealth, age and employment samples, the Lewbel IV method did not reject the assumption of exogeneity. We are therefore confident that we can rely on the probit estimates for inference.

Why was diabetes found to be exogenous in the Mexican case? We can only speculate on the potential reasons. Diabetes being exogenous seems to indicate that a person's employment status might not have such a strong effect on his or her diabetes risk through the potential pathways such as lifestyle changes. Rather, the rapid epidemiological transition experienced in Mexico over the last decades (Barquera et al., 2006; Barquera et al., 2008; Rivera et al., 2002) together with the heightened genetic susceptibility of Mexicans to diabetes (Williams et al., 2013), seem to have increased the risk of developing diabetes in both employed and unemployed Mexicans.

Taking our results for the older age group and comparing them to those of Brown et al. (2005b) for the USA, whose sample of Mexican Americans 45 years and older might be the best suited for a meaningful comparison, our findings indicate a stronger negative impact of diabetes on males and particularly females residing in Mexico.[9] This finding lends some support to our hypothesis that the adverse impact of diabetes on employment could be larger in LMICs than in high-income countries. Comparing the study to Lin (2011) for Taiwan, who also used a sample of people between 45 and 64 years of age, our results are similar in that a larger absolute effect is found for males than for females. However, when compared to other studies in more developed countries, with more advanced health systems and very different populations, such as Latif (2009) for Canada and Minor (2011) for women in the US, our results differ in that they do find effects for men and potentially also women.

While the results for women in the main analysis do not reach the levels of statistical significance that those for men do, the negative impact on women is supported by the subgroup analysis. When we take into account the lower overall female employment rates (31%) compared to men (80%), the absolute reduction in employment probabilities in women translates into an even larger relative decrease of over 16% for women compared to 12.5% for men. This suggests that diabetes has a considerable impact on employment probabilities of both men and women.

[9] This is based on comparing our estimates to the appropriate models in Brown et al. (2005b) based on their test for endogeneity, which indicates the use of the bivariate probit results for women and the probit results for men.

A limitation of this study is the use of cross-sectional data, which does not allow for the use of fixed effects and hence for the control of unobserved time-invariant heterogeneity. Data spanning a longer time period would be required to be able to observe changes in the diabetes and employment status which would allow the use of fixed effects. A further limitation is the somewhat old data from 2005, which precedes the main implementation period of the public health insurance scheme called Seguro Popular. This should be taken into account when interpreting our results as the effects might be different today, where most Mexicans have access to some sort of health insurance (Knaul et al., 2012). The presented results rather show the effects of diabetes on employment probabilities in 2005 in an environment were insufficient healthcare coverage was common for parts of the Mexican population. We nonetheless deliberately chose this particular dataset as it provided us with a sensible instrument in parental diabetes as well as an array of other socioeconomic information which—as far as we have been able to ascertain—is not provided by any other dataset in LMICs. Finally, due to data limitations, we were not able to investigate the relationship between diabetes duration and employment probabilities and how long it takes for an employment penalty to develop. Recent research by Minor (2013) on the US has shown that the effect of diabetes on employment probabilities changes with the duration of diabetes and is biggest in the first five years after diagnosis for males, whereas for females effects appear only about 11–15 years after diagnosis.

Looking ahead, it would evidently be worthwhile to investigate the effects of diabetes on employment in Mexico using more recent data. In light of the recently completed implementation of Seguro Popular—which increased its coverage from about 10 million people in 2005 to over 50 million in 2012 and now provides almost all previously uninsured Mexicans with access to healthcare (Knaul et al., 2012)—the results of this paper might be used as a baseline to judge the success of Seguro Popular in reducing the adverse effects of diabetes on employment.

In conclusion, this paper shows that diabetes represents a large burden for people in Mexico and likely in other LMICs, not only due to the associated disease and medical cost burden but also because of its effect on employment probabilities. This is particularly a problem for the poor who are more adversely affected by diabetes than the more affluent. To alleviate some of the negative effects of diabetes, Seguro Popular may provide an opportunity to further improve the prevention and treatment of diabetes for the poor, especially if the health system adapts to the challenges presented by chronic diseases (Samb et al., 2010). Evidence of possible cost-effective interventions for secondary prevention in the context of Seguro Popular already exists (Salomon et al., 2012). There remains, however, an evidence gap on cost-effective strategies for the primary prevention of diabetes.

4 The impact of diabetes on labour market outcomes in Mexico: a panel data and biomarker analysis

Pre-amble

This study builds on the results of the preceding chapter. Instead of using an instrumental variable (IV) approach to address the issue of endogeneity, it takes advantage of the recently released third wave of the Mexican Family Life Survey (MxFLS) to allow the construction of a longitudinal data set containing three waves. This enables the use of panel data methods to arrive at a potentially causal interpretation of the estimates, without having to rely on an IV approach.

Further, the study provides additional evidence for the effect of self-reported diabetes on wages and working hours in a developing country. Finally, it addresses another area identified by the systematic review in Chapter 2. Using biomarker data it investigates in how diabetes effects the labour market outcomes of the large undiagnosed population, also providing information about whether findings based on self-reported diabetes can be used to infer on the entire population with diabetes. This should help to better interpret estimates using self-reported diabetes as provided in Chapter 3.

Abstract

There is limited evidence on the labour market impact of diabetes, and existing evidence tends to be weakly identified. Making use of Mexican panel data to estimate individual fixed effects models, we find evidence for adverse effects of self-reported diabetes on employment probabilities, but not on wages or hours worked. Complementary biomarker information for a cross-section indicates that a large population with diabetes is unaware of the disease. The results indicate that the adverse effects found for self-reported diabetes do not extend to those unaware of their diabetes. Further analysis suggests that this difference stems from worse general health among the self-reports rather than more severe diabetes.

Introduction

Diabetes, and particularly its most common variant, type 2 diabetes, has increased worldwide and is expected to continue to rise over the next decades (NCD Risk Factor Collaboration, 2016). It has become a problem for middle-income countries (MICs) and high-income countries (HICs) alike, with over two-thirds of people with diabetes living in the developing world (International Diabetes Federation, 2014). Mexicans and Mexican-Americans appear to be particularly affected by diabetes, also in comparison to other Latino populations living in the USA (Schneiderman et al., 2014). In Mexico itself, diabetes prevalence has been estimated to have grown from 6.7% in 1994 to 14.4% in 2006, including both diagnosed and undiagnosed cases (Barquera et al., 2013), and is expected to increase further over the next decades (Meza et al., 2015). Already now, diabetes is the number one cause of death in Mexico (Barquera et al., 2013).

The observed trend has been attributed to a deterioration in diet and a reduction in physical activity (Barquera et al., 2008; Basu et al., 2013), while genetic predisposition among Mexicans with pre-Hispanic ancestry may also have played a role (Williams et al., 2013). Recent evidence indicates that the onset of diabetes has been occurring at an ever earlier age in Mexico (Villalpando et al., 2010). With treatment as ineffective as it currently is—only a minority achieves adequate blood glucose control (Barquera et al., 2013)—the earlier onset will increase the likelihood of complications during the productive lifespan.

Diabetes is a term used to describe various conditions characterized by high blood glucose values, with the predominant disease being type 2 diabetes accounting for about 90% of all diabetes cases (Sicree et al., 2011). The elevated blood glucose levels, that are a result of the body's inability to use insulin properly to maintain blood glucose at normal levels, can entail a range of adverse health effects for the individual concerned. However, via effective self-management of

the disease much if not all of the complications can be avoided (Gregg et al., 2012; Lim et al., 2011). In the absence of effective self-management—or in the case of inadequate treatment—diabetes has been documented to lead to conditions such as heart disease and stroke, blindness, kidney problems, and nerve problems which together with impaired wound healing can lead to the loss of limbs (Reynoso-Noverón et al., 2011). These conditions can be seriously debilitating and may therefore reduce an individual's economic activity, including its productivity and labour market participation.

The effect of diabetes on labour market outcomes has been studied predominantly in HICs—with the exception of a study on Mexico (Seuring et al., 2015b) and one on China (Liu et al., 2014) each. In the HIC studies diabetes has been found to be associated with reductions in employment probabilities as well as wages and labour supply (Brown et al., 2005b, 2011; Brown, 2014; Latif, 2009; Minor, 2011, 2013; Minor et al., 2016; Seuring et al., 2015a).

While these studies have provided useful evidence on the potential labour market effects of diabetes, many of the complexities of the relationship have not been comprehensively addressed in any given study. First of all, unobserved heterogeneity presents a challenge to estimate the relationship between diabetes and labour market outcomes. Especially time-invariant unobserved individual characteristics, e.g. health endowments—often related to health during uteru, infant and child years, and to low household income or adverse health shocks during these early years—as well as risk preferences, have been shown to adversely affect health in general and the propensity to develop type 2 diabetes more specifically (Ewijk, 2011; Li et al., 2010; Sotomayor, 2013). These and other unobserved personal characteristics (e.g. ability) may also affect employment probabilities, wages or working hours directly through their effects on contemporaneous productivity (Currie et al., 2013) and indirectly by limiting educational attainment and human capital accumulation (Ayyagari et al., 2011). Further, only focusing on the overall effect of a self-reported diabetes diagnosis does not reveal when potential labour market penalties appear, given the dynamic aspect of diabetes and the potential differences in its effects over time. Additionally, apart from its health impact, diabetes might also affect labour market outcomes through other channels. For instance, people aware of their condition may be less inclined to continue working if this interferes with their disease management, or could be suffering from psychological consequences (depression, anxiety) of becoming aware of the disease; they may also use the diagnosis as a justification for decreasing their labour supply, leading to a potential justification bias in the estimated effect of diabetes (Kapteyn et al., 2009). Importantly, for these reasons the labour market effects may also be distinct for people with self-reported versus those unaware of their condition, potentially leading to biased estimates if the analysis is solely

based on self-reports.

The objective of this study is to provide new evidence on the impact of diabetes on labour market outcomes, while improving upon previous work by paying close attention to the above challenges. We use three waves of panel data from Mexico covering the period 2002–2012, provided by the Mexican Family Life Survey (MxFLS). The MxFLS is particularly useful for the analysis of diabetes as it allows us to account for the above complexities in a more refined way than has been the case so far. Using individual level fixed effects (FE) analysis for the first time in this literature, we take account of time-invariant heterogeneity when assessing the impact of self-reported diabetes and self-reported diabetes duration on labour market outcomes.[1] Further, we add to the current literature in exploring the role of undiagnosed diabetes, using novel and rich biomarker data—an issue of considerable importance in light of the large prevalence of undiagnosed diabetes (see Beagley et al. (2014)) that remained unaccounted for in most earlier studies which typically relied on self-reported information. Doing so sheds light on the issue of measurement error and the potentially differential effects of self-reported and undiagnosed diabetes.

Our results using self-reported diabetes suggest an economically important decrease in the employment probability of people aware of their disease. Wages and working hours, however, do not appear to be negatively associated with self-reported diabetes. We further find that employment probabilities are reduced with each additional year since diagnosis, with some evidence for an even larger effect per year after the initial 10 years.

The biomarker analysis indicates that self-reported diabetes entails a significant employment penalty, while biometrically measured diabetes does not. Overall, undiagnosed diabetes does not appear to affect any of the labour market outcomes examined here, suggesting that adverse effects mainly occur to those self-reporting a diagnosis. We argue that, nonetheless, the effects found for self-reported diabetes in this study are largely unbiased as long as inference is not extended to the unobserved undiagnosed population, and are economically important in light of the sheer size of the diagnosed population in Mexico.

Diabetes and labour market outcomes—existing evidence

Several studies have investigated the effects of diabetes on labour market outcomes.

For the USA, Brown et al. (2005b) estimate the impact on employment in 1996–

[1] We are not aware of any other evidence on the effect on wages and working hours in a MIC.

1997 in an elderly population of Mexican Americans living close to the Mexican border, using a bivariate probit model. The study finds diabetes to be endogenous for women but not for men. For the latter, the estimates show a significant adverse effect of 7 percentage points. For women, the negative effect becomes insignificant when using IV estimation. In another study, again for a cross-sectional sample of Mexican-Americans, Brown et al. (2011) look at how diabetes management, inferred from measured glycated hemoglobin (HbA1c) levels, is associated with employment probabilities and wages. The authors detect a linear negative association between HbA1c levels and both employment probabilities and wages for men.

Two further studies also examine the impact of diabetes on employment and productivity for the USA: Minor (2011) focuses on the effect of diabetes on female employment, earnings, working hours and lost work days in 2006, finding diabetes to be endogenous and its effect underestimated if exogeneity is assumed. In the IV estimates, diabetes has a significant negative effect on female employment as well as annual earnings but not on working hours. In a later study, Minor (2013) investigates the relationship of diabetes duration and labour market outcomes using a cross-sectional analysis, providing evidence of a non-linear relationship, with employment probabilities declining shortly after diagnosis for men and after about 10 years for women; wages are not affected by duration. Finally, a recent study by Minor et al. (2016) investigates the association of self-reported diabetes and undiagnosed diabetes with employment probabilities and working hours in an adult USA population, using cross-sectional data. This study indicates a reduction in the coefficient size of diabetes if undiagnosed diabetes cases are included in the diabetes indicator instead of only self-reported diabetes. Further, they find that there is no association of undiagnosed diabetes with employment probabilities itself. However, the results of the study, particularly those for undiagnosed diabetes, are based on a very small number of cases, warranting further investigation.

For Canada, Latif (2009) estimate the effect of the disease on employment probabilities using an IV strategy similar to Brown et al. (2005b). His results suggest diabetes to be exogenous for females, and both endogenous and overestimated for males in the univariate model, with the estimates of the bivariate model indicating a significant negative impact on the employment probabilities for women, but not for men. For Australia, Zhang et al. (2009) analyse the effects of diabetes on labour force participation using a multivariate endogenous probit model. Their results demonstrate reduced labour market participation for males and females as a result of diabetes, with the effects appearing overstated if the endogeneity of diabetes is unaccounted for.

To the best of our knowledge only two studies exist for non-HICs. Liu et al.

(2014) investigate the effect of a diabetes diagnosis on labour income in China, exploiting a natural experiment to identify causality, finding a significant reduction in income for those with a recent diagnosis. An earlier study for Mexico explored the effect of self-reported diabetes on the probability of employment using only cross-sectional data from the 2005 wave of the MxFLS, and found a significant ($p<0.01$) reduction in employment probabilities for males by about 10 percentage points and for females by about 4.5 percentage points ($p<0.1$), using parental diabetes as an IV (Seuring et al., 2015b). The scarcity of evidence for low- and middle-income countries (LMICs) is also documented in a recent systematic review of the economic cost of diabetes (Seuring et al., 2015a).

Overall, the majority of existing studies, including those on high income countries, tend to suffer from at least four key limitations:

1. They rely exclusively on cross-sectional data, limiting the possibilities to account for unobserved individual characteristics.

2. The use of the family history of diabetes, which has been the sole instrumental variable employed so far, relies on the genetic and heritable component of type 2 diabetes that could theoretically provide valid identification of the true effect of diabetes. However, it remains unclear whether the variable fully satisfies the exclusion restriction, as it may also proxy for other genetically transferred traits, including unobserved abilities that impact labour market outcomes directly. This traditional identification strategy also abstracts from intrahousehold or intergenerational labour supply effects (Seuring et al., 2015b).[2]

3. The use of self-reported diabetes can introduce non-classical measurement error due to systematic misreporting which has been shown to cause estimates of economic impacts to be potentially biased and overstated (Cawley et al., 2015; O'Neill et al., 2013; Perks, 2015).

4. A final potential limitation lies in the selection into diagnosis as a result of disease severity: those who are more severely ill are more likely to have visited a medical doctor and be diagnosed.

To overcome some of these limitations, this paper applies an individual level FE panel estimation strategy and makes use of biomarker data. We also estimate models for different types of employment, i.e. non-agricultural wage employment, agricultural employment and self-employment, as ill health may have distinct effects across these activities.

[2]It is conceivable that diabetes might deteriorate parental health in such a way that the offspring either has to give up their employment to provide care, or has to increase labour supply to compensate for lost income.

Data

We use the Mexican Family Life Survey (MxFLS), a nationally representative, longitudinal household survey, which has three waves conducted in 2002, 2005–2006 and 2009–2012. All household members aged 15 and above were interviewed, covering information on a wide range of social, demographic, economic and health characteristics of the individuals and their families (Rubalcava et al., 2013). Apart from self-reported diabetes information that is available in all rounds, we also use information on the self-reported year of diagnosis as well as biomarker data including HbA1c levels for a subsample of respondents. Our main analysis uses all three waves, taking advantage of the large amount of observations and the panel structure of the data. Our variable of interest is self-reported diabetes, which is based on the survey question: "Have you ever been diagnosed with diabetes?".

Because we found some inconsistencies in the self-report of a diabetes diagnosis over time in a small subset of observations, we investigate and try to increase the consistency of the self-reported diabetes variable, using disease information from earlier and ensuing waves to infer on the current, missing or inconsistent, diabetes status (see page 269 in the Appendix for further details on our correction procedures). A further, and no less important, source of measurement error is the omission of those with undiagnosed diabetes. In order to investigate how this may affect estimates of the labour market impact of diabetes we use information from a subsample of the 2009-2012 wave, containing over 6000 respondents (everybody aged 45+ and a random subsample of those aged 15–44 (Crimmins et al., 2015)) that have biometrically measured blood glucose values, allowing for the identification of those with undiagnosed diabetes. Throughout our analysis the samples we use are restricted to the working age population (15–64). To prevent pregnant women from biasing our results due to the increased diabetes risk during pregnancy and its effects on female employment status, we have dropped all observations of women reporting to be pregnant at the time of the survey (N=764). We further exclude everybody currently in school.

The detailed information in the MxFLS allows us to consider the following outcome variables of interest: employment[3], hourly wage and weekly working hours[4].

[3]Employment status is defined as having worked or carried out an activity that helped with the household expenses the last week and working for at least four hours per week. This explicitly includes those employed informally, for instance people working in a family business or as peasants on their own land. The number of working hours needed to be considered as working is lower than in Chapter 3. We took this decision because we wanted to assess the impact of diabetes on driving people out of work completely. Any effect on working hours should be captured in the respective working hours models. We also tested if changing the definition of being employed to having worked at least ten hours per week as in Chapter 3. This only led to marginal changes in the coefficients and standard errors, not affecting the interpretation of the results.

[4]Hourly wage was calculated by adding up the reported monthly income from the first and

For the pooled data of all three waves (Table 14), diabetes was self-reported by 5% of men and 6% of women, respectively. This is consistent with other prevalence estimates of self-reported diabetes for this time period in Mexico.[5] About half of the respondents in the sample live in rural areas. Looking at our outcome variables, 86% of men report some form of employment compared to 37% of women. Interestingly, men do not report considerably higher hourly wages than women but work more hours per week. Also, men are working more often in agricultural jobs while women are more likely to be self-employed or in non-agricultural wage employment. Women also have lower educational attainment on average.

Turning to the biomarker subsample of the third wave (2009–2012), respondents are somewhat older on average than in the pooled sample, as it includes everybody above the age of 44 but only a random subsample of those aged 44 or below (Crimmins et al., 2015). Also, self-reported diabetes is higher than in the pooled sample[6]. Regarding the other control and outcome variables, the sample is fairly similar to the pooled sample. Remarkably, a relatively large share of people have an HbA1c indicative of diabetes, defined by the World Health Organization (WHO) as levels above or equal 6.5% (World Health Organization, 2011)[7]: 18% of males and females are unaware of their diabetes. This suggests that relying on self-reported diabetes as a measure for diabetes in Mexico might considerably understate the true extent of diabetes, potentially leading to biased estimates of its economic impact.

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second job (if any) and dividing it by the average number of weeks per month. This gave us the average earnings per week which were then divided by the weekly working hours to arrive at an hourly wage estimate. Labour income was either reported as the total amount for the whole month or more detailed, containing information on the monthly wage, income from piecework, tips, extra hours, meals, housing, transport, medical benefits and other earnings. Over 80% of respondents reported the total amount instead of a detailed amount. Respondents were also asked for their annual income and we used that information to arrive at an hourly wage if information for monthly labour income was missing. Those working self-employed or as a peasant on own land were also asked to provide their monthly and/or annual monetary income. We exclusively used information on monetary income provided in the survey, and consequently do not account for the value of agricultural produce used for the own consumption or the value generated by working in a family business without receiving any monetary remuneration. Finally, we adjusted the calculated wage for inflation from the year of the interview up to 2013 and took the log of those values. Due to a considerable number of missing or zero income reports the sample used for the wage estimation is smaller than the sample for working hours. Working hours were calculated summing up the self-reported working hours of the first and—if applicable—the second job. Working hours were calculated for every type of work, irrespectively of receiving a monetary remuneration or not.

[5] Barquera et al. (2013) show that the prevalence of diagnosed diabetes in Mexico was 7.5% in 2006, only somewhat above our results, which may be the result of the slightly different age groups considered.

[6] As well as in the full sample of wave 3.

[7] In one of the first analyses of these new biomarker data, Frankenberg et al. (2015) show that the rates of elevated HbA1c levels in Mexico are very high when compared to HbA1c data from similar surveys in the USA and China.

Table 14: Descriptive statistics for panel and biomarker sample.

	Panel		Biomarker	
	Males	Females	Males	Females
Dependent variables				
Employed	0.86	0.37	0.86	0.34
	(0.34)	(0.48)	(0.35)	(0.47)
Hourly wage (Mexican Peso)	42.47	40.49	36.30	35.23
	(485.87)	(142.08)	(53.69)	(43.63)
Weekly working hours	46.82	38.99	46.00	38.15
	(16.79)	(18.90)	(16.89)	(19.65)
Agricultural worker	0.22	0.04	0.25	0.03
	(0.41)	(0.20)	(0.43)	(0.18)
Self-employed	0.19	0.28	0.21	0.32
	(0.39)	(0.45)	(0.41)	(0.47)
Non-agricultural worker or employee	0.59	0.68	0.53	0.64
	(0.49)	(0.47)	(0.50)	(0.48)
Diabetes variables				
Self-reported diabetes	0.05	0.06	0.09	0.12
	(0.22)	(0.24)	(0.29)	(0.32)
Diabetes duration if self-reported diabetes (years)	7.49	7.83	7.48	7.99
	(6.01)	(7.83)	(6.07)	(7.03)
Glycated hemoglobin (HbA1c)			6.46	6.58
			(1.89)	(2.02)
HbA1c $\geq 6.5\%$			0.26	0.28
			(0.44)	(0.45)
Undiagnosed diabetes			0.18	0.18
			(0.39)	(0.39)
Education and demographic variables				
Age	36.03	36.29	42.78	42.79
	(13.62)	(13.17)	(14.28)	(13.94)
Rural village of $< 2{,}500$	0.44	0.43	0.50	0.46
	(0.50)	(0.50)	(0.50)	(0.50)
Married	0.54	0.54	0.60	0.56
	(0.50)	(0.50)	(0.49)	(0.50)
Number of children (age < 6) in household	1.48	1.57	1.18	1.22
	(1.45)	(1.47)	(1.29)	(1.32)
Indigenous group	0.19	0.19	0.19	0.18
	(0.39)	(0.39)	(0.39)	(0.39)
Secondary	0.30	0.30	0.26	0.26
	(0.46)	(0.46)	(0.44)	(0.44)
High school	0.16	0.13	0.14	0.12
	(0.36)	(0.34)	(0.34)	(0.33)
Higher education	0.11	0.09	0.12	0.09
	(0.32)	(0.29)	(0.32)	(0.28)
Observations	21388	27341	2785	3623

Notes Mean values, standard deviations in parenthesis. Results for the other variables, i.e. the Mexican states, log hourly wage and wealth, are omitted to save space.

Estimation strategy

Strauss et al. (1998) provide a useful framework to think about the relationship between health and labour market outcomes:

$$L = L(H, pc, w(H; S, A, B, I, \alpha, e_w), S, A, B, V, \xi) \tag{6}$$

where L is labour supply or labour market participation, pc is a vector of prices for consumer goods, w is the real wage, H is an array of measured health status, S is education, A is a vector of demographic characteristics, B is the family background of the individual, I captures the local community infrastructure, α is an array of unobservables (e.g. ability), e_w represents the measurement error, V is non-labour income and ξ is the taste parameter.

The equation showcases the joint effect of health on both wages and labour supply or labour market participation. Health affects labour supply and participation directly by impacting the ability to work and indirectly by changing wages.

There are several ways diabetes may affect H. First of all, diabetes can deteriorate health if it remains untreated, with the adverse effects becoming more severe over time. Second, a diagnosis of diabetes and ensuing treatment may lead to better health compared to the undiagnosed state. However, compared to healthy people even those receiving treatment for their diabetes may still have worse health outcomes. Third, there is also evidence that the diagnosis itself may affect one's own health perception and could lead to worse self-perceived health (Thoolen et al., 2006). We therefore expect diabetes to adversely affect health and consequently labour market outcomes.

When estimating equation 6 empirically with observational data, unobserved heterogeneity may bias the results. As mentioned in the introduction of this chapter, unobserved factors captured in α such as early childhood investments, innate ability and risk preference could affect wages as well as the probability to develop diabetes. Further, changes in wages or employment status may also affect the probability to develop diabetes by affecting dietary and physical activity patterns. Finally, measurement error e_w may be an important issue due to the large undiagnosed population with diabetes, particularly if being diagnosed is related to employment or wages via better access to healthcare through employment benefits and higher income.

The following section describes our estimation strategy for the different parts of the data.

Panel data on self-reported diabetes

We investigate the relationship between self-reported diabetes and three labour market outcomes: employment, wages and weekly working hours, respectively, using a FE model. While using individual level FE does not allow to fully identify a causal relationship, this strategy does improve on the degree of causal inference, compared to a simple cross-sectional analysis.[8] In particular it does allow controlling for unobserved personal characteristics that could bias the estimates, without the drawbacks of an at least debatable IV strategy that has been widely applied in this literature. We have also estimated random effects models but do not present them here as the Hausman test suggested the use of the FE model throughout.[9]

We estimate the following model:

$$Y_{it} = \beta_0 + \beta_1 Diabetes_{it} + \beta_2 X_{it} + c_i + \gamma_t + u_{it}. \tag{7}$$

where Y_{it} is a binary variable taking a value of 1 if respondent i reports being in employment at time t and 0 otherwise, $Diabetes_{it}$ is a binary variable taking a value of 1 at time t if the respondent reports having ever received a diagnosis of diabetes[10], X_{it} is a vector of control variables, c_i represents an individual fixed effect, γ_t represents year dummies, and u_{it} is the error term.

For the relationship of self-reported diabetes with wages and working hours our empirical models are estimated conditional on having positive wages and being employed, respectively. In these models Y_{it} represents the log hourly wage of respondent i at time t or the weekly working hours over the last year.

The control variables in both FE specifications include dummy variables to capture the effects of the living environment, of living in a small, medium or large city with rural as the reference category, and state dummies. We also include a marital status dummy and the number of children residing in the household below the age of 6 to control for the impact of marriage and children on labour market outcomes and the effect of childbearing and related gestational diabetes on the probability of developing type 2 diabetes (Bellamy et al., 2009). To account for the effect of changes in household wealth on diabetes and employment probabilities, we use standard principal component analysis of multiple indicators of household assets and housing conditions to create an indicator for household

[8] Other forms of unobserved heterogeneity could also affect our estimates—for instance time-variant unobserved heterogeneity or omitted variables simultaneously driving labour market outcomes and health.

[9] See the respective table for the results of the cluster robust Hausman test

[10] We are not able to distinguish between type 1 diabetes and type 2 diabetes using this data. Other studies that tried to assess the effect of type 1 diabetes on labour market outcomes have found no association (Minor, 2011; Minor et al., 2016). Including type 1 diabetes therefore likely attenuates any adverse relationship we may find.

wealth[11] (Filmer et al., 2001). Finally, a quadratic age term and calendar year dummies are included to capture the non-linear effect of age and any trends over time, respectively.

Before moving on, it bears emphasizing that despite our efforts to reduce any bias in our estimates, the estimated coefficients do not reflect true causal effects since time-variant unobserved heterogeneity may still bias the estimates. With respect to employment status, one potential issue would be that job loss affects lifestyle choices that increase the probability to develop diabetes, which could then in turn negatively affect labour market outcomes. So far, the evidence of the health effects of job loss does not indicate important effects of job loss on the probability to develop diabetes (Bergemann et al., 2011; Schaller et al., 2015), but this has so far only been researched in a high-income country context. Another example relates to stress at work, which has been linked to the development of type 2 diabetes (Eriksson et al., 2013; Heraclides et al., 2012). However, while stress levels may change over time, a person's coping mechanisms to deal with stress are likely time-invariant (Schneiderman et al., 2005). While we cannot exclude the role of these time variant unobserved factors, it seems that the role of time-invariant variables, e.g. genetic predisposition and relatively stable personality traits, is predominant. The applied FE approach should then limit the bias resulting from these time-invariant confounding factors.

Self-reported diabetes duration

To explore the role of the duration of diabetes for labour market outcomes, we estimate the following model using a self-reported measure of the years since diagnosis:

$$Y_{it} = \beta_0 + \beta_1 Dyears_{it} + \beta_2 X_{it} + c_i + u_{it}, \tag{8}$$

where $\beta_1 Dyears_{it}$ is a continuous variable indicating years since first diabetes diagnosis.

In an effort to capture possible non-linearities in the relationship of interest we then use a spline function that allows for the effect of an additional year with diabetes to vary over time.

$$Y_{it} = \delta_0 + g(Dyears_{it}) + \delta_2 X_{it} + c_i + u_{it}. \tag{9}$$

with $g(Dyears_{it}) = \sum_{n=1}^{N} \delta_n \cdot max\{Dyears_{it} - \eta_{n-1}\} I_{in}$ and $I_{in} = 1[\eta_{n-1} \leq$

[11] Our composite wealth index consists of owning a vehicle, a second house, a washing machine, dryer, stove, refrigerator or furniture, any electric appliances, any domestic appliances, a bicycle or farm animals. It further accounts for the physical condition of the house, proxied by the floor material of the house, and the type of water access.

$Dyears_{it} < \eta_n]$, with η_n being the place of the n-th node for $n = 1, 2, \ldots, N$. We choose three nodes that—based on visual inspection (see Figures 5, 6 and 7 on pages 111, 112 and 113, respectively)—best captured any possible non-linearity in the relationship between diabetes duration and labour market outcomes. These are located at 4, 11 and 20 years after diagnosis. The first four years should capture any immediate effects of the diagnosis, the years five to eleven should capture any effects of adaptation to the disease. After 11 years it is conceivable that many of the debilitating complications of diabetes would appear that could deteriorate health and lead to adverse effects on labour market outcomes. The coefficient δ_n captures the effect of diabetes for the n-th interval. The effects are linear if $\delta_1 = \delta_2 =, \ldots, = \delta_n$.

Because the year of diagnosis was only reported in the third wave, duration of diabetes (or time since diagnosis) for the earlier waves was only calculated for those that had also been interviewed in the third wave, reducing the comparability of the results to those using the binary diabetes indicator.[12]

One caveat of using FE is that, when year dummies are included, any variable that varies by one unit in each time period is not separately identified (Wooldridge, 2012). Because this is also the case for diabetes duration, in equation (8) and equation (9) identification of this variable relies on the presence of people without diabetes in the sample, for which diabetes duration does not increase at the same rate as time.[13] As a robustness check, we also estimate two models that only use between-individuals variation, i.e. a linear probability model (LPM) that uses only data from the third wave, the only wave where year of diagnosis was originally reported, and a pooled LPM that used data from all three waves.[14]

Cross-section: biomarker and self-reported data

Self-reported diabetes only captures part of the population with diabetes as many individuals remain undiagnosed; it may also contain cases of people who misreport having diabetes. Estimations based on self-reports may therefore suffer from selection bias in at least three ways:

1. Systematic overreporting of diabetes: people without diabetes may report a diabetes diagnosis, unintentionally—for instance due to a misdiagnosis, either from a health professional or because of self-diagnosis, or

[12] To obtain the time passed since diagnosis, the year of diagnosis was subtracted from the year of the interview.

[13] Consequently, those that reported a diagnosis in the year of the interview were counted as 'one year since diagnosis'. From this follows that if the respondent reported to having been diagnosed in the year before the interview he or she was counted as 'two years since diagnosis' and so on.

[14] Models also excluding the calendar year dummies provide similar results.

intentionally—for instance with a view to justifying some other adverse event or status in their life (e.g. being unemployed).

2. Systematic underreporting of diabetes: people with diabetes may also underreport because they are concerned about negative stigma associated with the condition. Furthermore, diabetes often remains undiagnosed leaving people unaware of their condition.

3. Diagnosis is more likely for those who are more likely to have visited a doctor, for instance because they are more affected by the condition, wealthier, or hypochondriac.[15]

Overreporting may attenuate the effect of diabetes if those falsely reporting a diabetes diagnosis are in fact in good health; it may also lead to an overestimation of the impact if some of those misreports reflect other factors that negatively affect labour market outcomes (e.g. other illnesses or general ill health), or if they are used to justify other adverse events that may negatively affect labour market outcomes. Similarly, underreporting may lead to an overestimation if those with undiagnosed diabetes are generally healthier, hence more likely to have positive labour market outcomes than those with self-reported diabetes. However, if the undiagnosed and the diagnosed groups are similar in terms of health, then this would lead to an underestimation of the effect of diabetes.

The health information received at a diabetes diagnosis may also have an effect in itself. It may for instance affect an individual's psychology which in turn may influence economic behaviour. Two studies found a diabetes diagnosis and subsequent treatment to increase the odds of psychological problems, including depression and anxiety (Paddison et al., 2011; Thoolen et al., 2006), while similar results have not been found for people with undiagnosed diabetes (Nouwen et al., 2011). Looking at behavioural change, health information has been shown to affect behaviour after the diagnosis of not only diabetes (Slade, 2012) but also of other chronic diseases (see Baird et al. (2014), Gong (2015), Thornton (2008), and Zhao et al. (2013b)). However, little is known about the effects of health information on labour market outcomes. For diabetes, only Liu et al. (2014) investigate the effect of receiving a diabetes diagnosis on labour income in Chinese employees. This study finds a reduction in labour income which was attributed to the psychological effects of the diagnosis.[16]

[15] More formally, assume that the true model of the effect of diabetes on labour market outcomes is $y = X^*\beta + \epsilon$. Because we do not observe the true values of X^* we have to use self-reported measures that contain errors: $X = X^* + u$. Since u may be correlated with ϵ - in contrast to classic measurement error which is randomly distributed, we cannot sign the bias of β.

[16] In a very different context Dillon et al. (2014), using a randomized intervention, find that the news stemming from a diagnosis of malaria affect productivity and income, but not labour supply among sugar cane cutters in Nigeria.

The use of biomarker data allows to explore the relationship of measured diabetes with labour market outcomes which can then be compared to the estimated effect of self-reported diabetes. The biomarker data also enable us to look at diabetes severity, as measured by HbA1c values. Since these data are only available for a subsample of one wave—the most recent one—our analysis here is limited to cross-sectional data no longer directly comparable to the panel-based results in this paper. Nonetheless, the data allow for a first exploration of the relationships of measured diabetes and disease severity with labour market outcomes.

Our analysis of the biomarker sample consists of three steps. We first estimate equation 10 to assess the association of self-reported diabetes with labour market outcomes as before, but this time for the biomarker sample only, using the following specification:

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 X_i + c_i + u_i. \tag{10}$$

We then estimate the relations between diabetes, as defined by our biomarker, and labour market outcomes, via the following equation:

$$Y_i = \beta_0 + \beta_1 Dbio_i + \beta_2 X_i + c_i + u_i. \tag{11}$$

Here $Dbio_i$ is equal to 1 if HbA1c $\geq 6.5\%$.

To find the effect of undiagnosed diabetes, we include both variables at the same time and estimate:

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 Dbio_i + \beta_3 X_i + v_i + u_i. \tag{12}$$

For the biomarker analysis we rely on within-community variation v_i for identification in order to account for unobserved community characteristics, such as the access to healthcare and the quality of healthcare in the community, poverty and unemployment levels in the community, or the amount of public green space and recreational possibilities available. These factors potentially affect both the propensity to develop diabetes and to receive a diagnosis; they may also be related to labour market outcomes.[17]

[17] We did not account for fixed household characteristics as the average number of observations per household was close to one, i.e. for most households only one member provided biomarker information in our subsample, significantly limiting the variation within households that would be needed for identification.

Results

Incidence of self-reported diabetes

Table 15 presents the estimation results of the FE model using equation 7. They indicate significant and substantial reductions in the probability of employment for men and women with self-reported diabetes. The coefficients are similar for both sexes, showing a reduction in employment probabilities of over 5 percentage points. In relative terms—taking into account the lower employment rates for women compared to men—these absolute reductions translate into relative reductions in employment probabilities of 14% for women and of 6% for men, suggesting a stronger impact of diabetes on women than men.

The results in Columns 3–6 show no significant relationship between self-reported diabetes and wages or working hours. One may expect this relationship to differ by the type of work, as those with diabetes working in an agricultural job that requires strenuous physical efforts may see their productivity more adversely affected than those engaged in more sedentary work. We therefore estimate a model including interaction terms between self-reported diabetes and agricultural employment and between self-reported diabetes and self-employment, respectively, using non-agricultural wage employment as the comparison group, and restricting our sample to those employed only.

The results in Table 16 show that while male agricultural workers have lower wages in general, the relationship with diabetes does not depend on the type of work, as none of the interaction terms show up as significant. In the working hours regression, one interaction term is significant, suggesting that those with self-reported diabetes working in agriculture supply 5 hours less relative to non-agricultural workers and employees. However, because we have more than two work types we cannot draw conclusions solely on the basis of the t-statistic. We therefore perform a Wald test for the overall significance of the interaction term which does not reject the null of no interaction effects ($p = .15$), indicating that the effect of diabetes on working hours does not vary significantly by type of work.

In summary, we find no evidence for an association between self-reported diabetes and wages or working hours. This lack of effects may be explained by selection: potentially, only those with 'mild' or asymptomatic diabetes are still in the same job continuing to earn similar wages. Only once complications become increasingly severe would they switch activity (or drop out of the labour market), without going through a notable phase of reduced productivity and labour supply.

To explore whether diabetes affects the selection into certain types of work we

estimate FE models of the probability of being in non-agricultural wage employment, agricultural employment or self-employment, using three dummy variables indicating the respective type of work as the left hand side variables. The results in Table 17 indicate a negative association with self-employment, though the estimates are quite imprecise. For women, those who self-report diabetes are less likely to work in agriculture and potentially self-employment. This may suggest that having diabetes drives people out of self-employment and agricultural jobs, for instance because these jobs are physically more demanding and possibly also because they provide less protection in terms of insurance and employment duration.[18][19]

[18] We also estimated a pooled multinomial logit model augmented with the within-between approach (Bell et al., 2015), based on the work of Mundlak (1978), which allows interpreting the coefficients of all time-varying variables as within-effects by including individual means of all time-varying covariates. Several other studies in economics have used this approach recently, e.g. Boll et al. (2016), Geishecker et al. (2011), and Wunder et al. (2014). The results indicate a very similar pattern both in size and significance.

[19] Using the same methods, we also investigated the impact of diabetes on changes in the type of work for those already employed, finding no evidence that diabetes leads to changes in the type of work.

Table 15: Self-reported diabetes and labour market outcomes.

	Employment		Log hourly wages		Weekly working hours	
	(1) Males	(2) Females	(3) Males	(4) Females	(5) Males	(6) Females
Self-reported diabetes	$-.054^{**}$	$-.059^{**}$	0.054	0.081	$-.524$	-1.955
	(.025)	(.024)	(.067)	(.158)	(1.499)	(2.517)
Hausman test	255.260	388.822	1084.317	91.096	967.007	106.455
p-value	0.000	0.000	0.000	0.000	0.000	0.000
N	21388	27341	13828	7068	17616	9112

Notes Individual level fixed effects. Robust standard errors in parentheses. Reference category: dependent non-agricultural worker or employee. Other control variables: state dummies, urbanization dummies, education dummies, married dummy, number of children < 6, wealth, health insurance status, age squared and calender year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Effect of self-reported diabetes on wages and working hours, by type of work.

	Log hourly wage		Weekly working hours	
	(1) Males	(2) Females	(3) Males	(4) Females
Agricultural worker	−.078*	−.280	−3.577***	−4.473*
	(.044)	(.186)	(.800)	(2.702)
Self-employed	0.028	−.144*	−1.452**	−4.713***
	(.043)	(.087)	(.704)	(1.388)
Self-reported diabetes	0.105	0.064	0.617	−.524
	(.076)	(.169)	(1.606)	(2.252)
Self-reported diabetes x agricultural worker	−.242	−.409	−5.495*	−3.535
	(.188)	(.373)	(2.833)	(22.300)
Self-reported diabetes x self-employed	−.105	0.125	0.306	−4.149
	(.192)	(.326)	(2.503)	(4.739)
Hausman test	280.491	912.537	4086.461	995.171
p-value	0.000	0.000	0.000	0.000
N	13828	7068	17616	9112

Notes Individual level fixed effects. Robust standard errors in parentheses. Reference category: non-agricultural worker or employee. Other control variables: state dummies, urbanization dummies, education dummies, married dummy, number of children < 6, wealth, health insurance status, age squared and calender year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Relationship between self-reported diabetes and selection into types of work.

	Males			Females		
	(1) Non-agric.	(2) Agric.	(3) Self-employed	(4) Non-agric.	(5) Agric.	(6) Self-employed
Self-reported diabetes	−.006	−.008	−.043	−.001	−.022**	−.029
	(.029)	(.022)	(.026)	(.018)	(.009)	(.018)
Hausman test	2196.390	2005.383	1249.080	1126.933		86.400
p-value	0.000	0.000	0.000	0.000		0.000
N	20719	20719	20719	26577	26577	26577

Notes Individual level fixed effects. Robust standard errors in parentheses. Other control variables: state dummies, urbanization dummies, education dummies, married dummy, number of children < 6, wealth, health insurance status, age squared and calender year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Duration of self-reported diabetes

Because diabetes is a chronic and generally life-long disease, we investigate how soon after the first diagnosis diabetes may affect labour market outcomes. Given that complications of diabetes develop over time, the effect may increase linearly as the years go by. Non-linear relationships are also plausible: health problems that have led to the diagnosis as well as psychological effects after the diagnosis may affect labour market outcomes immediately after having been diagnosed with diabetes. Similarly, management of the disease may be successful only after some initial period. It is also possible that after some time complications start to appear, again reducing health and leading to reductions in labour supply and productivity.

To obtain an initial idea of the relationship between our outcome variables and diabetes duration we use a non-parametric kernel-weighted local polynomial regression. As Figure 5 shows, the relationship between diabetes duration and the probability of employment for men shows a more or less steady decline that becomes more pronounced as time progresses. For women, a first drop-off occurs right after diagnosis; thereafter no consistent pattern is observed.[20] A similar analysis for wages shows somewhat more erratic relationships, although there seems to be a long term negative trend for women but not for men (see Figure 6). Similar trends are observed for working hours (see Figure 7).

Tables 18 and 19 present the results of the linear and non-linear duration models (for which we created the following splines to capture the immediate, intermediate and long-term relationships: 0–4, 5–11, 12–19 and 20+), starting with the results of the cross-sectional LPM, followed by the pooled LPM and then the FE model as specified in equation (8) and equation (9).

For male employment probabilities (Table 18) the results indicate a yearly reduction throughout all models, with the biggest effects being suggested by the FE model. For women, the coefficient shows a reduction of up to almost 1 percentage point per year in the FE model, though statistical significance is lower than in the ordinary least squares (OLS) models. Focusing on the FE results, the coefficients in the spline models provide some evidence for an immediate effect of diabetes, which then levels off for some time after which it becomes stronger again. Nonetheless, for males and particularly females, the coefficients are quite imprecisely measured.

Turning to wages (Table 19), the FE model indicates a reduction in female wages of about 7% per year with diabetes. For men we find no consistent effect. The results of the non-linear specification indicate that there may be a reduction

[20] Since long run estimations suffer from large standard errors—as the sample size is strongly reduced—this limits its interpretation and we therefore truncate the graphs at a disease duration of 24 years.

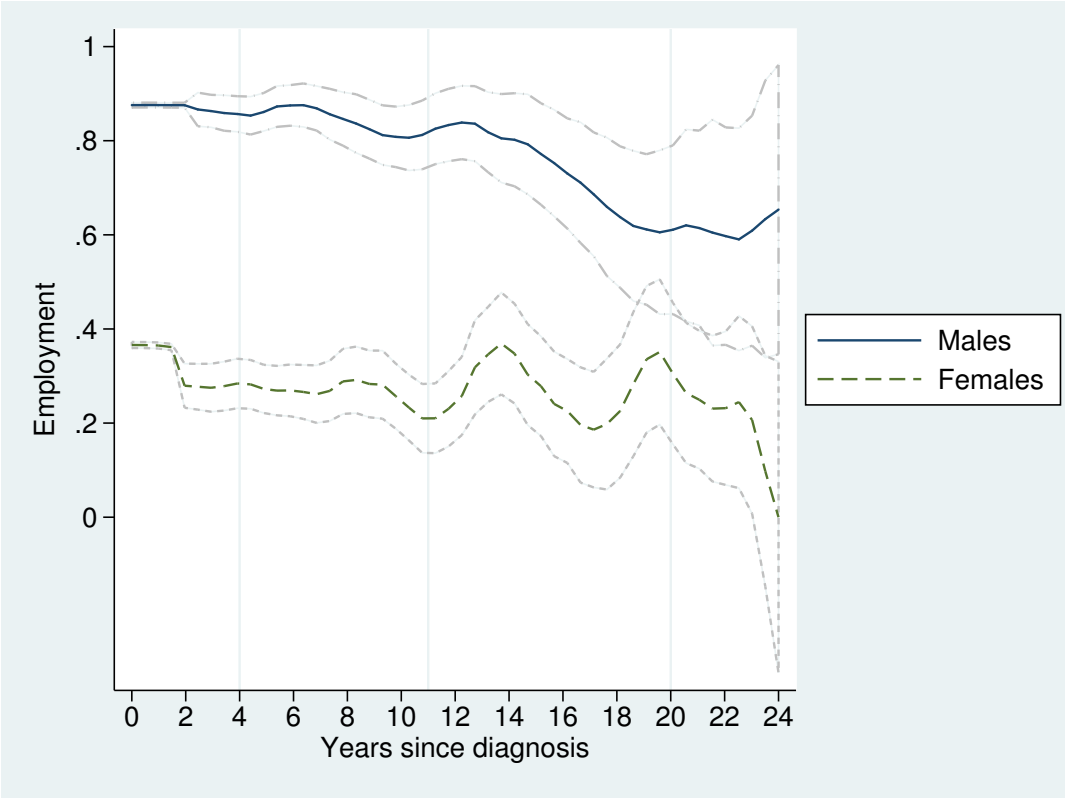
in wages 5–11 years after the initial diagnosis for both men and women. We also find associations for women with more than 20 years of diabetes, but these estimates may be spurious due to the considerably reduced number of observations in this group.[21] Interestingly, the reductions in wages found in the non-linear specification appear exactly at the time where employment probabilities are less affected. This could suggest that at this point reductions in productivity affect wages but are not so severe that they would cause job loss. There appears to be no consistent relationship between working hours and time since being diagnosed with diabetes.

Overall, these results suggest a fairly constant decrease in the probability of employment for both men and women and in earnings for women, which contrasts with estimates for the USA (Minor, 2013), where no such linear relationship is observed. Minor (2013) finds a reduction in employment probabilities of 82 percentage points for females after 11 to 15 years and a reduction of 60 percentage points for males after 2-5 years, indicating very large employment penalties, in particular in comparison to our results for Mexico. However, our non-linear results are not directly comparable to these estimates as Minor used pooled cross-sectional data, constructed dummy variables instead of splines and used different duration groups.[22]

[21] There are only 9 and 3 observations for male and female wages with more than 20 years since diagnosis in wave 3, respectively, and 17 and 7 in the pooled sample, respectively. For male and female working hours there are 12 and 7 observations with more than 20 years since diagnosis in wave 3, respectively, and 20 and 12 for the pooled sample, respectively.

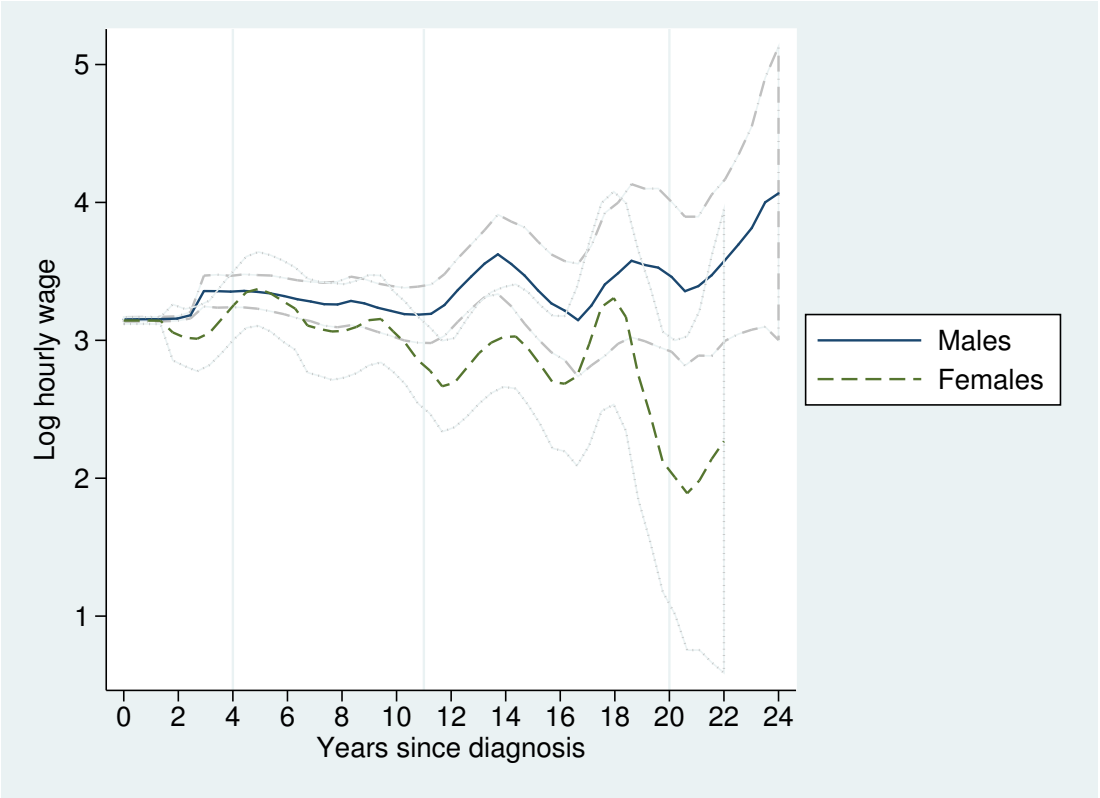
[22] We estimated a comparable model to that of Minor (2013) using dummy variables and find a significant reduction in employment probabilities throughout, regardless of whether we use our duration groups to construct the dummies or the duration groups used by Minor (2013). For men, we find a significant reduction of about 6 to 12 percentage points, depending on the specification used, in the first 2 and 4 years after diagnosis, respectively. In the following years the effect size tends to increase somewhat. For women, we find less evidence for an immediate effect of diagnosis, but effects do emerge after about 2 years of living with the disease and also increase somewhat over time.

Figure 5: Kernel-weighted local polynomial regression of employment status on diabetes duration.



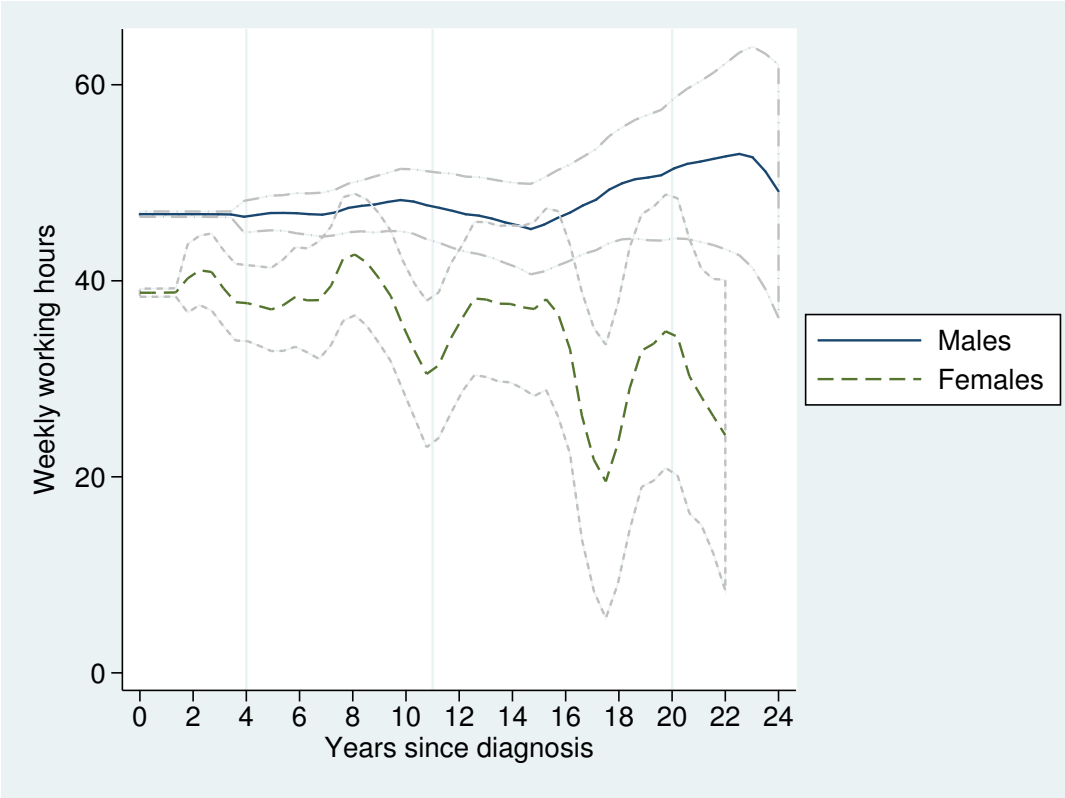
Notes The dotted lines around the main line show 95% confidence intervals.

Figure 6: Kernel-weighted local polynomial regression of log hourly wages on diabetes duration.



Notes The dotted lines around the main line show 95% confidence intervals.

Figure 7: Kernel-weighted local polynomial regression of working hours on diabetes duration.



Notes The dotted lines around the main line show 95% confidence intervals.

Cross-sectional biomarker analysis

In this section we gain additional insights from using the biomarker data collected in the third wave of the MxFLS. These data enable us to identify respondents with HbA1c levels equal to or above the internationally recognized diabetes threshold of 6.5%. This will allow the investigation of the direction of bias introduced when relying on self-reported diabetes only and when it is not possible to identify those unaware as well.

We first present a cross tabulation of self-reported diabetes and the results of the biomarker analysis (Table 20). The table shows that 27% of the sample have HbA1c levels indicative of diabetes and 81% of those self-reporting a diabetes diagnosis also have HbA1c levels equal to or above the diabetes threshold. Overall, of the people with diabetes according to the biomarker analysis, 32% self-report a diagnosis, while 68% do not.

To further investigate the relationship of self-reported and biomarker tested diabetes, we estimate the models presented in equations 10, 11 and 12. The results in columns 1 and 2 of Table 21 show that the earlier longitudinal results using self-reported diabetes are robust for the biomarker sample. The coefficients in column 3 and 4 indicate that the associations with employment probabilities are much weaker when using diabetes defined by the biomarker instead of self-reported diabetes.[23] In columns 5 and 6, obtained from estimating equation 12, the coefficient for the biomarker diabetes population $Dbio_i$ now reflects the effect of undiagnosed diabetes, as the regression includes a control for self-reported diabetes, revealing that undiagnosed diabetes is not associated with any of the labour market outcomes.

[23] We also created a dummy variable that additionally to measured diabetes accounted for those with a self-reported diabetes diagnosis but biomarker levels below the diabetes threshold. This allowed us to investigate the effect for the entire population with diabetes. The coefficients and their statistical significance are only marginally different to those presented in columns 3 and 4 of Table 21, which is why we do not present them here.

Table 18: Relationship between self-reported years since diagnosis and employment probabilities using continuous duration and duration splines.

	Males			Females		
	(1) OLS (Wave 3)	(2) OLS (Pooled)	(3) FE	(4) OLS (Wave 3)	(5) OLS (Pooled)	(6) FE
Panel A: linear						
Diabetes duration	−.008***	−.007***	−.017***	−.005***	−.004***	−.009*
	(.002)	(.002)	(.006)	(.002)	(.001)	(.005)
Hausman test			153.024			200.073
p-value			0.000			0.000
Panel B: splines						
Diabetes duration						
0–4	−.007	−.007	−.026*	−.010	−.015**	−.017
	(.007)	(.006)	(.014)	(.007)	(.006)	(.016)
5–11	0.000	−.003	−.003	−.004	0.004	−.003
	(.009)	(.006)	(.009)	(.008)	(.006)	(.008)
12–20	−.030**	−.017*	−.029*	0.005	−.004	−.014
	(.012)	(.010)	(.016)	(.008)	(.006)	(.011)
> 20	0.011	0.007	−.046*	−.010*	−.003	−.015
	(.016)	(.014)	(.028)	(.006)	(.003)	(.018)
Hausman test			161.953			198.692
p-value			0.000			0.000
N	8217	16292	16292	10467	22407	22407

Notes The table presents the results of three estimation methods. Panel A presents the results of the linear specifications. Panel B presents the results of the non-linear specifications. Robust standard errors in parentheses. Other control variables: state dummies, urbanization dummies, education dummies, married dummy, number children < 6, wealth, age squared and calendar year dummies. The OLS and pooled OLS models additionally control for age. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Relationship between self-reported years since diagnosis and log hourly wage / weekly working hours using continuous duration and duration splines.

	Males			Females		
	(1) OLS (wave 3)	(2) OLS (pooled)	(3) FE	(4) OLS (wave 3)	(5) OLS (pooled)	(6) FE
			Log hourly wages			
Panel A: linear						
Diabetes duration	0.001	0.010**	−.019	−.014*	−.009	−.073**
	(.006)	(.005)	(.018)	(.008)	(.008)	(.029)
Hausman test			838.213			93.232
p-value			0.000			0.000
Panel B: splines						
Diabetes duration						
0–4	0.034*	0.046***	0.033	0.027	0.030	0.015
	(.017)	(.016)	(.055)	(.031)	(.026)	(.138)
5–11	−.041*	−.037**	−.055*	−.039	−.034	−.101*
	(.021)	(.018)	(.033)	(.030)	(.024)	(.056)
12–20	0.015	0.044	0.062	−.032	−.071*	−.051
	(.033)	(.029)	(.056)	(.042)	(.039)	(.047)
> 20	0.053	0.014	−.111	−.007	0.041***	−.204***
	(.054)	(.040)	(.104)	(.028)	(.015)	(.053)
Hausman test			1037.290			96.266
p-value			0.000			0.000
N	5509	10767	10767	2874	5741	5741
			Weekly working hours			
Panel A: linear						
Diabetes duration	0.069	0.048	0.181	−.020	−.124	0.208
	(.124)	(.102)	(.330)	(.187)	(.127)	(.652)
Hausman test			704.904			107.709
p-value			0.000			0.000
Panel B: splines						
Diabetes duration						
0–4	−.033	−.233	0.709	0.739	0.470	2.014
	(.421)	(.325)	(.938)	(.645)	(.586)	(2.947)
5–11	0.269	0.338	−.218	−.410	−.479	−.508
	(.539)	(.399)	(.568)	(.728)	(.553)	(1.020)
12–20	0.209	0.137	0.698	−.164	−.051	−.402
	(.730)	(.538)	(.945)	(.995)	(.700)	(1.207)
> 20	−1.300	−.768	0.039	−.499	−.418	8.117***
	(.944)	(.930)	(2.184)	(.930)	(.305)	(1.612)
Hausman test			724.225			112.627
p-value			0.000			0.000
N	6807	13581	13581	3591	7383	7383

Notes The table presents the results of three estimation methods for the two dependent variables: log hourly wages and weekly working hours. Panel A presents the results of the linear specifications. Panel B presents the results of the non-linear specifications. Robust standard errors in parentheses. Other control variables: state dummies, urbanization dummies, education dummies, married dummy, number children < 6, wealth, age squared, calendar year dummies, type of work (agricultural and self employed with dependent non-agricultural wage employment as the base) and health insurance status. The OLS and pooled OLS models additionally control for age. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Number of observations with diabetes (HbA1c $\geq$ 6.5%) and self-reported diabetes.

	$HbA1c < 6.5\%$	HbA1c $\geq 6.5\%$	Total
No self-reported diabetes	4544	1181	5725
	79%	21%	100%
	97%	68%	89%
Self-reported diabetes	129	554	683
	19%	81%	100%
	3%	32%	11%
Total	4673	1735	6408
	73%	27%	100%
	100%	100%	100%

Notes The first row of each category presents absolute values, the second row presents row percentages and the third row present column percentages.

As discussed earlier, differences in effects between self-reported diabetes and those undiagnosed are likely to stem from selection into the diagnosed population, for instance those in worse health, with higher HbA1c levels or a longer disease duration are more likely to go to the doctor and be diagnosed as well as to lose their job because of their diabetes. To further explore this, we first estimate models additionally controlling for self-reported health status, to capture differences in subjective individual health. Secondly, we estimate models accounting for measured HbA1c levels, to investigate in how far current diabetes severity affects our labour market outcomes. If current severity would be related to labour market outcomes and explain the difference between self-reported and undiagnosed diabetes, one would expect an adverse association with increasing HbA1c levels, for both self-reporting and undiagnosed. To investigate this, we construct three dummy variables using HbA1c groups above the diabetes threshold (i.e. 6.5–7.9, 8–11.9 and 12–14), each for those with self-reported diabetes and for those unaware of their diabetes (Table 22, Panel B).

When additionally controlling for subjective health status, we find that for men and women the difference between self-reported diabetes and undiagnosed diabetes is reduced due to a smaller coefficient for self-reported diabetes (Table 22, Panel A). Especially for women, the point estimates for self-reported diabetes and undiagnosed diabetes are now virtually the same size, suggesting that differences could be due to the differences in self-reported health. For men, factors not captured by self-reported health may still play a role.[24]

Turning to Panel B, we do not find a consistent relationship of increasing HbA1c levels with employment chances, especially for those self-reporting, suggesting that current disease severity may not explain the different employment effects of diabetes for the aware and unaware.

To the best of our knowledge only one study has previously used biomarkers to analyse the relationship with labour market outcomes in a comparable population. Brown et al. (2011) use data for a Mexican American population in a broadly comparable way to this paper, though stopping short of investigating the labour market impact of undiagnosed diabetes. In concordance with our results, this study also finds that once diabetes is diagnosed, current management plays a minor role in determining labour market outcomes. This is not surprising given that HbA1c levels only provide a picture of blood glucose levels over the last three months. They therefore may not be representative of blood glucose levels in the years before and after the diabetes diagnosis which ultimately determine how soon complications appear and how severe they will be.

[24] Additionally accounting for measures of overweight and obesity, self-reported hypertension, heart disease and depression does not further affect the interpretation of the diabetes coefficient.

Table 21: Biomarker results

	Self-reported diabetes		HbA1c $\geq$ 6.5		HbA1c $\geq$ 6.5 and self-reported d.	
	(1) Males	(2) Females	(3) Males	(4) Females	(5) Males	(6) Females
Dependent variable: Employment						
Self-reported diabetes	−.051**	−.044*			−.053**	−.032
	(.026)	(.023)			(.026)	(.026)
HbA1c $\geq$ 6.5			−.012	−.031*	0.003	−.022
			(.016)	(.018)	(.017)	(.019)
N	2785	3623	2785	3623	2785	3623
Dependent variable: Log hourly wages						
Self-reported diabetes	−.010	−.040			−.006	−.010
	(.065)	(.113)			(.078)	(.119)
HbA1c $\geq$ 6.5			−.007	−.057	−.006	−.055
			(.044)	(.070)	(.049)	(.075)
N	1803	884	1803	884	1803	884
Dependent variable: Weekly working hours						
Self-reported diabetes	−.293	−.751			−.286	−1.566
	(1.305)	(2.178)			(1.419)	(2.351)
HbA1c $\geq$ 6.5			−.088	1.153	−.012	1.525
			(.844)	(1.462)	(.925)	(1.565)
N	2302	1144	2302	1144	2302	1144

Notes Community level fixed effects. Robust standard errors in parentheses. Other control variables: age, age squared, state dummies, urbanization dummies, education dummies, married dummy, number children < 6 and wealth. Calender year dummies are included as data collection for the third wave was stretched out over several years. The wage and working hour models additionally control for type of work (agricultural and self employed with non-agricultural wage employment as the base) and for health insurance status. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22: Self-reported diabetes, biomarkers, diabetes severity and self-reported health and their association with labour market outcomes

	Employment		Log hourly wages		Weekly working hours	
	(1) Males	(2) Females	(3) Males	(4) Females	(5) Males	(6) Females
Panel A (self-reported health)						
Self-reported diabetes	−.036	−.023	0.002	0.060	0.123	−2.191
	(.026)	(.027)	(.079)	(.121)	(1.433)	(2.386)
HbA1c $\geq$ 6.5%	0.003	−.023	−.004	−.051	−.066	1.829
	(.017)	(.019)	(.049)	(.075)	(.926)	(1.569)
Self-reported health status						
good	0.023	0.057*	0.061	−.115	−1.131	3.521
	(.025)	(.034)	(.074)	(.124)	(1.376)	(2.499)
fair	−.007	0.006	0.025	−.157	−1.606	4.646*
	(.026)	(.034)	(.076)	(.128)	(1.424)	(2.607)
bad	−.127***	−.024	−.016	−.371*	−6.190**	6.918*
	(.043)	(.046)	(.135)	(.189)	(2.521)	(3.858)
very bad	−.165	0.117	−.331	0.316	−1.869	−17.400*
	(.110)	(.116)	(.300)	(.439)	(6.433)	(9.005)
N	2785	3621	1803	883	2302	1143
Panel B (HbA1c levels)						
Self-reported diabetes						
6.5 − 7.9	−.126**	−.040	−.228*	0.041	1.218	−9.170*
	(.059)	(.051)	(.127)	(.269)	(2.921)	(4.864)
8 − 11.9	−.052	−.051	0.026	0.225	−1.332	−1.086
	(.051)	(.042)	(.107)	(.206)	(2.298)	(4.395)
12+	0.011	0.021	−.106	−.427	1.979	−2.518
	(.062)	(.069)	(.156)	(.279)	(3.692)	(5.335)
Undiagnosed diabetes						
6.5 − 7.9	0.005	−.002	0.015	−.040	1.003	3.616
	(.022)	(.025)	(.058)	(.099)	(1.178)	(2.323)
8 − 11.9	0.006	−.027	0.014	−.204	−1.004	−.077
	(.035)	(.031)	(.078)	(.129)	(1.485)	(2.614)
12+	0.015	−.055	−.019	0.169	−1.581	1.753
	(.040)	(.046)	(.087)	(.181)	(2.099)	(3.978)
N	2785	3623	1803	884	2302	1144

Notes Community level fixed effects. Robust standard errors in parentheses. Other control variables: age, age squared, state dummies, urbanization dummies, education dummies, married dummy, number children < 6 and wealth. Calender year dummies are included as data collection for the third wave was stretched out over several years. The wage and working hour models additionally control for type of work (agricultural and self employed with non-agricultural wage employment as the base) and for health insurance status. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Minor et al. (2016) finds for a general USA population, similar to us, that people with undiagnosed diabetes likely, if at all, experience smaller employment penalties than people self-reporting the disease. He finds, however, much bigger effects than we do when estimating the impact of biometrically measured diabetes instead of distinguishing between the self-reporting and those unaware. This may be explained by the fact that in that study the undiagnosed population made up a much smaller share of the overall population with diabetes compared to our study, so that self-reported diabetes was still the predominant factor driving the result.

Conclusion

Diabetes has become one of the most common chronic diseases in middle- and high-income countries, with the potential to severely impact the health and economic well-being of those directly (and possibly indirectly) affected. Yet there remains only limited 'hard' evidence on the economic consequences, especially for these countries. Moreover, what evidence does exist at best partially tackles the econometric challenges involved.

This paper improves on existing work by addressing several methodological challenges that arise due to the nature of the disease and types of data available, using rich longitudinal panel data from Mexico, a MIC for which the biomarker data used in this paper indicates that diabetes, including undiagnosed diabetes, has reached alarming levels.

Apart from providing unique evidence for a developing country, the paper makes methodological contributions for the estimation of labour market effects of diabetes. By estimating individual fixed effects the analysis provides an improved accounting for the endogeneity of self-reported diabetes, as this allows cancelling out the potential role of unobserved individual traits that may affect both labour market outcomes and the propensity to self-report (or suffer from) diabetes. Using further information on the year of diagnosis enables us to investigate the potential heterogeneity in the effect of self-reported diabetes on labour market outcomes over time. Finally, taking advantage of biomarker data to identify the entire population with diabetes, i.e. including those with undiagnosed diabetes, allows for an assessment of the potential bias in estimates relying on self-reported diabetes (which is still the most frequent measure in the previous literature).

The first part of our results confirms a considerable gap in employment probabilities for both men and women reporting a diabetes diagnosis, compared to those that do not report the condition. We also find some evidence that diabetes is more likely to reduce the probability of employment in the agricultural and self-employment sector, characterized predominantly by informal arrangements,

compared to the rest of the workforce. Those who remain employed do not suffer any wage or labour supply effects, possibly because they are still relatively healthy or are able to resort to a type of work that does not entail their diabetes status limiting their work-related performance. More research will be needed to confirm and further investigate this finding as well as its interpretation.

Regarding the heterogeneity in the effects of diabetes over time, our results indicate an adverse impact of self-reported diabetes on employment chances, with the impact growing in magnitude especially after the first 10 years post-diagnosis. This is plausible in that as time lived with diabetes evolves, complications associated with diabetes tend to become more frequent and more severe (Adler et al., 2003). Looking at wages as our labour market outcome, we uncover some adverse effects for females, indicating a sizeable reduction with time since diagnosis. These findings may bode ill for countries where diabetes has started appearing at an increasingly younger age, causing people to live with the disease for larger parts of their productive lifespan, possibly exacerbating the economic effects of reduced employment due to diabetes (Hu, 2011; Villalpando et al., 2010).

The second part of our results indicates that only relying on self-reported diabetes can lead to an overestimation of the relationship between diabetes and labour market outcomes. We find that a negative relationship only exists for those with self-reported, but not for those with undiagnosed diabetes. This perhaps surprising, notable difference, is at least mediated by the subjective health status being worse for those self-reporting compared to the undiagnosed. Current disease severity, as proxied by HbA1c levels, does not appear to play an important role in this context.

Our findings bear several implications. First, when interpreting labour market impact estimates relying on self-reported diabetes, one cannot assume that the results extend to those with undiagnosed diabetes. However, the strategy of simply merging those self-reporting and those undiagnosed in one diabetes category may not be ideal either, as doing so will fail to account for the heterogeneity between the groups in the amount of health information they possess, the time they have already been exposed to elevated blood glucose levels and consequently their subjective as well as true health status, leading to a potentially important loss of information. If, by contrast, both groups are separately accounted for in the model, thereby acknowledging their inherent differences, this allows us to gain information about the distribution of the economic burden across the two groups.

In the case of Mexico, given that more than 7% of the Mexican population have been diagnosed with diabetes, the identified reduction in employment probabilities for those with self-reported diabetes still amounts to a significant overall economic burden being associated with (diagnosed) diabetes.

Our results add further weight to the case for reducing the incidence and progression of diabetes. On top of the well-documented health benefits, it appears there are considerable potential gains to be had in terms of increasing the productive lifespan of people. This is of particular importance in LMICs, where parental health shocks, related job loss and increasing health expenditures can have repercussions across the entire household. Other family members, including children, may be forced to increase their labour supply and to reduce non-health expenditures in order to prevent deterioration of the household's economic situation. This can lead to forgone investments into child education, showcasing the potential for adverse long-term effects of health shocks due to diabetes (Bratti et al., 2014). Moreover, the large proportion of undiagnosed people indicates that diagnosis—at least in Mexico—happens too late or not at all, thereby significantly reducing the possibility to prevent complications via appropriate treatment and self-management, which has repercussions by increasing the risk of severe complications appearing early. Hence, much of the health and economic burden may be prevented by earlier diagnosis and, given the generally limited success in achieving good control in Mexico, better treatment of those already diagnosed with diabetes. Ultimately, of course, there will be a need to invest in the prevention of diabetes cases in the first place. Taxation of sugar sweetened beverages may be one promising way forward (Colchero et al., 2016), though the long-term effects in terms of diabetes prevention remain to be demonstrated.

5 The relationship between diabetes, employment status and behavioural risk factors: An application of marginal structural models and fixed effects to Chinese panel data

Pre-amble

Chapters 3 and 4 provided evidence of the adverse impact of self-reported diabetes on employment probabilities in Mexico. However, if this is also the case in other middle-income countries (MICs) is unclear. Chapter 5 adds to this using panel data covering a period of rapid economic transition in China, again estimating the relationship of diabetes and employment status. Moreover, it provides information about the ability of people with diabetes achieving changes in behavioural risk factors important for the prevention of diabetes complications, as studies have shown that smoking cessation and weight loss after a diagnosis can have beneficial effects on blood glucose control and the risk of complications. Importantly, it not only addresses time-invariant unobserved heterogeneity by using individual level fixed effects as in the previous chapter, but also accounts for the potential effects of time-variant confounding by using marginal structural models.

This method is widely applied in epidemiology and able to account for confounding over time, where prior outcomes can affect the current treatment, for example the previous employment status affects the current diabetes status. This potential source of bias has been assumed to not exist in previous studies, but could potentially have biased the estimate of the effect of diabetes on labour market outcomes. This chapter thereby makes several contributions compared to the previous chapters: It provides information about the robustness of the identified

relationship of diabetes with employment status by using an alternative estimation strategy in a different setting, thereby also taking into account the potential effect of behavioural risk factors, and it gives first evidence in how far people with diabetes in China are able to change their behavioural risk factors after a diabetes diagnosis.

Abstract

A diabetes diagnosis entails important consequences for its recipients. Diagnosed patients obtain health information but also face the challenge of having to manage the condition via lifestyle adjustments, with potential consequences for—among other things—their economic activity. We investigate the causal effect of a diabetes diagnosis on employment status and behavioural risk-factors, two potentially intertwined factors, using longitudinal data from the China Health and Nutrition Survey (CHNS) that cover the years 1997 to 2011. Two complementary statistical techniques—marginal structural models and fixed effects panel estimation—are used for the statistical analysis, and generate very similar results despite their different underlying assumptions. Both strategies find distinct patterns for males and females. They suggest a decrease in female employment probabilities after a diagnosis (over 11 percentage points) and further show that women are mostly unable to positively change their behavioural risk factors by loosing weight and reducing energy intake. Men, however, do not see their employment probabilities affected by diabetes and also respond to a diagnosis by losing weight and reducing energy intake as well as their intake of alcohol in ways that are sustained over time. These results suggest important inequities in the impact of diabetes between sexes in China and point to the potential of reducing behavioural risk factors for women to narrow these inequities.

Introduction

The effect of diabetes on employment status has received relatively little attention in middle-income countries (MICs), including China. The scarce existing evidence indicates that diabetes can affect labour market outcomes in high-income countries (HICs), but also in MICs (Seuring et al., 2016). This is of growing relevance especially with diabetes appearing increasingly earlier in a person's productive lifespan, likely due to increasing obesity at earlier ages. Importantly, once diagnosed, the onset of diabetes and diabetes complications, strongly depends on the patient's behaviour. Behavioural risk factors, like alcohol consumption, smoking, caloric consumption and weight gain, are all related to the onset of diabetes as well as ensuing diabetes complications. Research shows, for instance, that behaviour changes after a diabetes diagnosis can have positive health effects and reduce the risk of subsequent cardiovascular events (Long et al., 2014) and may help in effectively managing blood glucose levels and achieving further treatment goals (Zhou et al., 2016). Consequently, if these risk factors can be reduced it may be possible to prevent some of the health and economic burden of diabetes. Thus, it seems that a diabetes diagnosis may present an important opportunity

to reduce risk factors for diabetes complications (De Fine Olivarius et al., 2015) and hence also reduce the economic burden of diabetes to the individual. This raises the question how a diabetes diagnosis affects both labour market outcomes and health behaviour over time.

However, one of the challenges of determining a causal relationship between diabetes, employment status and changes in behavioural risk factors is their potential bidirectional interrelatedness. For example, employment status might be affecting weight status by reducing the time spend on physical activity due to reductions in available leisure time, or it may promote risk factors such as smoking behaviour or energy intake that can both affect the probability of developing diabetes as well as diabetes related complications, for instance by increasing stress levels. In an effort to investigate the dynamic impact of unemployment on health behaviours, Colman et al. (2014) found heterogeneous effects of unemployment which led to slight weight gain, a decrease in smoking and decreases in fast-food consumption. Macroeconomic evidence also indicates that job loss can lead to changes in health, especially in mental health (Charles et al., 2008), which may have further downstream effects on health behaviours.

Research on the impact of diabetes on labour market outcomes has so far ignored the potentially simultaneous relationship of diabetes with employment and behavioural diabetes risk factors. Using regression techniques, such as ordinary least squares (OLS) or fixed effects (FE), it was assumed that the investigated independent variables are unaffected by prior values of the dependent variable. However, if prior changes in employment status are causally related to a diabetes diagnosis or affect the risk factors for diabetes complications, not accounting for this can lead to biased estimates.[1] Similarly, studies investigating the impact of a diabetes diagnosis on behavioural risk factors while not taking into account the effect of employment status on both diabetes and these risk factors, may produce biased estimates. Moreover, apart from time-varying confounding due to observed covariates, unobserved variables present a further challenge. In particular, time-invariant confounders—such as poor early life conditions or personal traits—may simultaneously increase the probabilities to develop diabetes, to be unemployed and to engage in unhealthy behaviour.

The goal of this study is therefore to assess the impact of a diabetes diagnosis on both employment probabilities and behavioural risk factors while accounting for the potentially intertwined relationships between diabetes, employment

[1] One solution is to include lagged values of the dependent variable on the right hand side, but this raises challenges of its own, including difficulty of interpretation, but also potentially biased estimates. The lagged dependent variable will be correlated with the time-invariant part of the error-term, violating the assumption of exogeneity of the right-hand side variables. Further, if the other covariates are correlated with the lagged-dependent variable, they will also be biased (Anderson et al., 1982; Nickell, 1981).

and health behaviours. This is done via the use of marginal structural models (MSMs), an estimation strategy that is increasingly common in epidemiology and is able to account for time-dependent confounding across time (Robins et al., 2000) when estimating the impact of a treatment, here a diabetes diagnosis, on the outcome of interest. This is, by our knowledge, the first time this estimation strategy is used to estimate the impact of diabetes on an individual's employment status or behavioural risk factors. We complement this strategy and test the robustness of the MSM estimates to the potential violation of one of its crucial assumptions, namely that there are no unmeasured confounding factors. To do this, we compare the MSM estimates with FE models which, although unable to account for the potentially bidirectional relationship, account for unobserved time-invariant confounding factors in addition to confounding due to observed variables. Very different results to the MSM would suggest a violation of the assumption of no unobserved confounding. To further investigate and understand the role of confounding factors, we also estimate random effects (RE) models and compare the results. We thereby further extend the evidence base for the impact of diabetes on labour market outcomes in MICs, where currently empirical information is only available for Mexico (Seuring et al., 2016). At the same time, the study provides, as far as we are aware, the first longitudinal evidence for the effect of a diabetes diagnosis on behavioural risk factors in any low- and middle-income country (LMIC).

More information about the effects of a diabetes diagnosis may be particularly important for LMICs such as China, where diabetes prevalence has surged from 1% in the early 1980s to about 10% in recent years (Hu, 2011; NCD Risk Factor Collaboration, 2016). Confronting this diabetes epidemic puts a strain on healthcare systems (Seuring et al., 2015a), increasing the need to find highly cost-effective prevention and treatment options applicable in MICs (Silink et al., 2010). However, to do this it is important to assess how successful people with diabetes currently are in preventing adverse economic effects and reducing their risk factors for diabetes complications.

The literature trying to identify a causal relationship between diabetes and employment has relied on instrumental variable (IV) strategies (Brown et al., 2005b; Latif, 2009; Seuring et al., 2015b) and individual FE models (Seuring et al., 2016). However, while an IV approach could potentially account for all forms of confounding, the validity of the instruments used is at least questionable (see discussion in Chapter 4). The FE model, as discussed above, also relies on important assumptions that may be violated. Turning to the relationship between a diabetes diagnosis and behavioural risk factors, only one study has intended to causally relate a recent diabetes diagnosis with changes in health behaviours, finding positive behaviour changes shortly after diagnosis in a USA population.

The effects were mostly short lived and tended to dissipate over time, particularly considering weight loss (Slade, 2012). To isolate the causal effect, Slade (2012) created an 'at risk' control group without diabetes that was intended to be similar to the treatment group with diabetes, apart from not having received a diagnosis. He used information on diabetes biomarkers to estimate the propensity score of those without a diabetes diagnosis to be above a specific at risk threshold, so that everybody above a certain propensity score was used to form the control group. He then estimated dynamic population average models, including the lagged dependent variable on the right hand side, as well as FE models to identify a causal relationship. While this approach likely improves the control group by increasing its similarity in the diabetes risk profile to the diagnosed population, the use of a lagged dependent variable may have biased the estimates due to unobserved time-invariant variables being correlated with the lagged dependent variable, violating the exogeneity assumption and potentially introducing bias in the other covariates. This is also true for the FE model (Anderson et al., 1982; Nickell, 1981). Further, the study did not account for employment status as one of the control variables.

A different identification approach was used by Zhao et al. (2013b) when investigating the effects of a hypertension diagnosis on nutritional outcomes in China. They used a regression-discontinuity design and biomarker information on blood pressure. A crucial assumption in that study was that people above the hypertension threshold were indeed informed about their hypertension while those just below the threshold were not. These two groups were then compared to isolate the particular effect of the additional health information on food consumption in the following wave. The results indicated that a diagnosis leads to reductions in fat consumption, but no other nutritional outcomes, and only for those economically better off. Several caveats exist for this study and the used approach. According to Zhao et al. (2013b), it was not always clear to what extent participants were informed about their hypertension status and whether they had received just the actual blood pressure measurement information, leaving the interpretation to the participants, or whether they were made explicitly aware of their hypertension (or also pre-hypertension) status. Further, the results may have limited generalisability, since the measured treatment effect may have been a very local one, depending on the representativeness of the population distribution below and above the threshold of the overall population above the threshold. In the case of significant differences between the populations, the results would only be applicable to the population around the hypertension threshold. Finally, the study only provides information for a relatively short period until the first wave after diagnosis, unable to capture any changes further away from the point of diagnosis.

Accordingly, there is a need to provide new evidence on the effects of a diabetes diagnosis on employment status as well as behavioural risk behaviours that could affect the development of diabetes complications, using longitudinal data and alternative estimation strategies. Thereby this study adds in several ways to the existing literature. First, it shows the impact of a diabetes diagnosis on labour market outcomes in China, not only over the short term, but for a period covering the entire decade of the 2000s, allowing for a more long term investigation of the effects. This both confirms and extends earlier evidence for other settings and using different methods. Second, it provides information on the effect of a diabetes diagnosis on health behaviours. Third, by considering the effects over time on both employment and health behaviour, the results shed light on potential pathways through which the impact on employment may work. Fourth, the study provides a methodological innovation by using both MSM and FE estimation methods, offering insights not only on the robustness of the MSM results, but also on the validity of some of its assumptions.

Methods

Study sample

The China Health and Nutrition Survey (CHNS) is an international collaborative project, led by the Carolina Population Center at the University of North Carolina at Chapel Hill, investigating nutrition and health behaviours in nine provinces of China (Zhang et al., 2014). We use data from 1997 onwards, which was the first time survey participants provided diabetes information. In total we use six waves (1997, 2000, 2004, 2006, 2009 and 2011) obtained from the longitudinal dataset released in 2015. The data provide extensive information on nutrition and health, and also include anthropometric measures of weight and height that reduce potential measurement issues plaguing self-reported data. The dataset further provides socioeconomic information, most importantly for this study about employment. The sample is limited to the adult population aged 18–64. The sample is not nationally representative and as such does not provide sampling weights (Popkin et al., 2010).

Overall, 84% to 90% of the survey participants were followed up in the consecutive wave, with attrition being highest after 2006. Attrition in the CHNS due to mortality was around 1% (Popkin et al., 2010). Other reasons mentioned by Popkin et al. (2010) are loss in follow up due to migration, natural disasters and redevelopment of housing in the urban centres leading to relocations. We investigated whether any of our variables of interest were significantly related to attrition at any wave. Lower calorie consumption and being unemployed were

associated with attrition. Further, attrition was strongly related to urbanization, a higher level of education, being of younger age and having lower family income, suggesting that mostly participants of younger age, more urbanized but from less well-off households tended to leave the survey. Having diabetes was not related to attrition. Attrition rates between the waves are shown in Table A16 in the appendix.

Assessment of diabetes

We used self-reported information on a diabetes diagnosis to construct our diabetes indicator. We only relied on incident cases of self-reported diabetes, excluding individuals with self-reported diabetes at baseline. Given the chronic nature of diabetes, we assumed that after the initial diagnosis diabetes persists for the rest of one's life. This is a reasonable assumption given the medical evidence (Steven et al., 2016).[2] To construct a measure of diabetes duration for incident cases we used self-reported information on the year of diagnosis. If we found that the year of diagnosis was reported to be before the last wave without a reported diagnosis or if the year of diagnosis was not reported, we used the midpoint between the last wave without diagnosis and the first wave with a diagnosis as the year of diagnosis.[3]

Assessment of outcomes

The economic outcome of interest is employment status, and is measured through self-reported response stating whether the respondent is currently working. Respondents who reported not to be working because they were students are excluded, while those who are not working for any other reason, such as doing housework, being disabled or being retired, are included.

The behavioural risk factor outcomes we estimate are current smoking status, if alcohol was consumed equal to or more than three times per week[4], body mass index (BMI), waist circumference in centimetres and daily calorie consumption. Smoking status and alcohol consumption are self-reported, while BMI and waist circumference are based on anthropometric measurements, minimizing potential reporting errors and indirectly indicating dietary and activity behaviour. Waist circumference is reported in centimetres. Finally, daily calorie consumption is

[2]Recently, a study showed successful remission of at least 6 months in some patients after the initiation of a very low-calorie diet (Steven et al., 2016). However, while this shows that type 2 diabetes may be reversible, this cannot be expected for patients diagnosed and currently treated in any healthcare system.

[3]The number of observations replaced at each wave was: 21 (2000), 44 (2004), 51 (2006), 78 (2009), 59 (2011). Overall it affected 43% of the self-reports of the year of diagnosis.

[4]We also estimated models investigating alcohol cessation instead of alcohol reduction, suggesting very similar effects.

a constructed variable, available in the CHNS, based on the average daily consumption of carbohydrates, protein and fat of every individual in the survey, measured on three consecutive days. As robustness tests, we also considered binary overweight and obesity indicators instead of the continuous BMI and waist circumference variables. We applied thresholds suggested by the China Obesity Task Force of a BMI ≥ 24 to define overweight and a BMI ≥ 28 to define obesity (China Obesity Task Force, 2004). Since there is considerable discussion about the correct thresholds to use for Asian populations to define overweight and obesity (He et al., 2015; World Health Organization, 2004; Zeng et al., 2014), we do not include these results in our main analysis but report them in the appendix (page 285).

Statistical analysis

Our analysis focuses on two statistical approaches to account for potential confounding and selection bias: marginal structural models (MSMs) and fixed effects (FE). Additionally, also RE models are estimated.

Marginal structural models

MSMs apply inverse probability of treatment weights (IPTW) to adjust for confounding and selection bias as a result of time-varying confounders being affected by prior exposure to the treatment (Robins et al., 2000). Under the assumptions of the MSM (Robins et al., 2000)—the reported treatment is the treatment that has actually been received (consistency), there are no unmeasured confounders (exchangeability) and every person in the sample has a non-zero chance of receiving the treatment (positivity) (see the Discussion section for a discussion of the validity of these assumptions in our case)—the causal direct acyclic graph (DAG) shown in Figure 8 displays the association between confounders and outcomes and a diabetes diagnosis.

In our context it seems possible that, for example, BMI could affect the probability of being diagnosed with diabetes which then itself may affect subsequent BMI levels, confounding the relationship between a diabetes diagnosis and BMI due to non-random selection. Similarly, employment history and current employment could affect the probability of a diabetes diagnosis through their impact on lifestyle and hence diabetes risk factors. For example, an increase in disposable income or a reduction in leisure time as a result of a new job and the subsequent effect on risk behaviours, such as weight gain or higher alcohol consumption, could confound the relationship between a diabetes diagnosis and employment status. MSM accounts for this by calculating inverse probability weights based on the potential risk of a person being diagnosed at each point in time, estimated

by logistic regression.

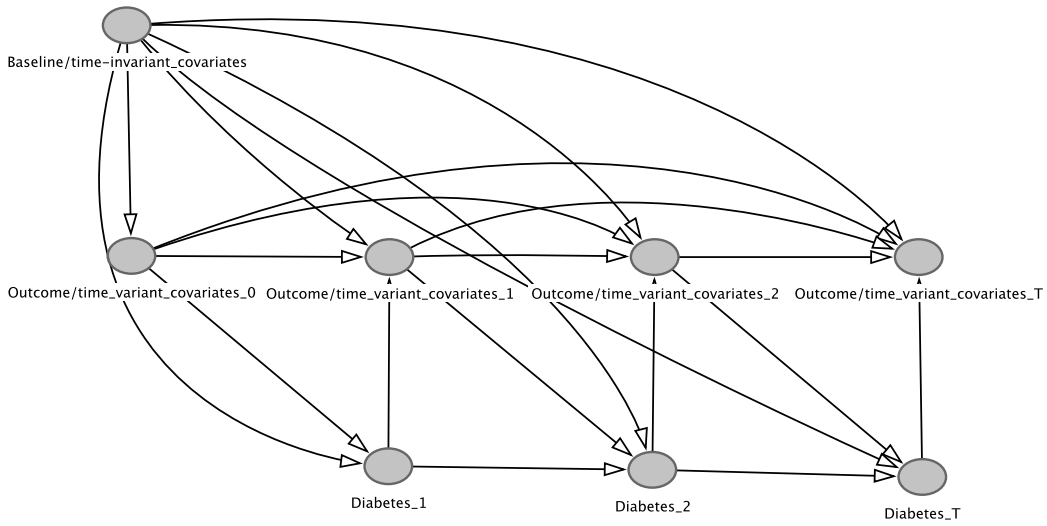
For the estimation of MSMs, first *unstabilized* IPTW for being diagnosed with diabetes are calculated for each individual at each wave. The IPTW are proportional to the inverse of the probability of a person having her own observed exposure through that wave and allow the creation of a pseudo population that is exchangeable with the study population within the levels of confounders (Cole et al., 2008). The *unstabilized* IPTW are using time-variant confounders measured at baseline, time-variant confounders lagged by one period, and time-invariant confounders as right-hand side variables to predict the cumulative probability of developing diabetes at each wave. We use lagged time-variant confounders to make sure that the predictors of diabetes were determined previous to the manifestation of diabetes. Otherwise, because the diagnosis happened at an unknown point of time between two waves, the key assumption that the time-variant variables used to predict the probability of a diabetes diagnosis are determined before the diabetes diagnosis may have been violated.

The *unstabilized* IPTW are calculated using the following predictors: age and age squared to account for changes in risk with increasing age; an index of urbanization pre-constructed within the CHNS data, ranging from 1 to 120 as the level of urbanization increases (Zhang et al., 2014), to account for the impact of urbanization on diabetes risk (Attard et al., 2012); binary variables for secondary and university education, being married, having any medical insurance, being of Han ethnicity, living in a rural area, the different Chinese regions and the respective survey waves; inflation adjusted per-capita household income to adjust for any effects of household wealth on diabetes; and employment status, alcohol consumption, smoking status, BMI, waist circumference and average daily calorie consumption. To create IPTW that account for each individual's entire reported history of diabetes risk factors, cumulative probabilities of diabetes are calculated by multiplying the predicted probabilities in the current and all previous waves, for each wave after the baseline wave.[5]

Because *unstabilized* IPTW can be highly variable and therefore less precise, it is recommended to stabilize the weights, especially when the predicted probabilities of exposure are close to zero (Cole et al., 2008). To calculate *stabilized* IPTW, an additional set of IPTW are created by predicting the diagnosis of diabetes using only baseline values of time-variant and time-invariant confounders as right-hand side variables. Similar to the calculation of *unstabilized* IPTW, cumulative probabilities are calculated by multiplying the predicted probabilities in the current and all previous waves, for each wave after the baseline wave. To calculate *stabilized* IPTW the just created weights are divided by the *unstabilized*

[5]To calculate the inverse probability weights we followed the Stata code provided by Fewell et al. (2004).

Figure 8: Direct acyclic graph for the marginal structural model



Notes MSMs assume the absence of unobserved time-invariant and unobserved time-variant confounders but allow the past treatments to affect the current outcomes (arrows going from Diabetes to time-variant covariates in the same wave) and the past outcomes to affect the current treatment (arrows going from time-variant covariates to Diabetes). Lagged time-variant covariates, baseline and time-invariant covariates predict current diabetes status.

IPTW. The resulting *stabilized* IPTW now only reflect the confounding due to the time-varying covariates, which cannot be appropriately adjusted for by standard regression models (Cole et al., 2008). Because our analysis is stratified by males and females, we create separate weights for each gender.

The MSMs for any of the outcome variables are then estimated adjusting for any baseline and time-invariant confounders used in the calculation of the IPTW, except for the respective outcome of interest, and weighted by the *stabilized* IPTW to adjust for time-variant confounding. OLS regression models are used for continuous outcomes (BMI, waist circumference and calorie consumption) and a logistic model for the binary outcomes (employment status, smoking status and alcohol consumption). For the logistic model we calculate average marginal effects for greater comparability with the results of the FE models. Robust standard errors to account for intra-class correlation of repeated outcome measurements in individuals are used throughout. In our primary analysis, we present the results of the MSM with untruncated stabilized weights, as these provide theoretically unbiased estimates, albeit they may be less efficient than truncated weights if the IPTW have a wide range considerably diverting from 1 (Cole et al., 2008). Given that our IPTW do not include very extreme values and have a mean weight of 1 (see Table A18), using untruncated weights likely leads to very little loss in efficiency in our case, supporting the decision to use untruncated weights in our primary analysis.

Fixed effects

While the MSM can account for pre-treatment selection on observable and time-variant confounders, it assumes that there are no unobserved time-invariant confounders such as family background, cognitive abilities, and other personal characteristics. This is a strong assumption that might be violated in practice. The individual level FE model can help remedy this problem as it is able to account for both observed time-variant and invariant variables as well as time-invariant unobserved variables as shown in the DAG in Figure 9. It does so by demeaning all covariates at each time point with the overall individual mean across all observed time points. It then uses solely the within-person variation for identification, thereby accounting for any time-invariant observed or unobserved as well as observed time-variant effects.

This comes at a price: due to the demeaning, time-invariant variables, such as Han ethnicity, are dropped from the model and their association with the outcomes cannot be estimated. Further, because the FE model is not able to account for any effects of a diabetes diagnosis on other time-variant confounders, only a more limited set of confounders can be included compared to the MSM.

Otherwise the estimates of the effect of a diabetes diagnosis would likely be biased due to the inclusion of 'bad controls'. Bad controls are control variables that have been affected by the treatment itself—such as BMI or smoking status after a diabetes diagnosis—and therefore likely capture part of the causal effect of diabetes on the outcome of interest, biasing the diabetes coefficient (Angrist et al., 2009). Also age is dropped from our FE estimations because in FE models two or more variables that change at the same rate between waves cannot be separately identified. In our case this applies for age and time-dummies, as both variables increase by one unit each additional year (Wooldridge, 2012). Consequently, for the estimation of the effect of time since diagnosis, we have to rely on the presence of people without diabetes in the sample, for which diabetes duration does not increase at the same rate as time. Our FE specifications thus only include controls for age squared, the level of urbanization, education, being married, having any medical insurance, living in a rural area, region and time dummies as well as per capita household income. FE models also make another assumption, which has received much less attention, namely that there is no dynamic causal relationship between treatment and outcomes, i.e. that past treatments have no direct effect on current outcomes, and that past outcomes have no direct effect on current treatment. If this assumption is violated, then results based on FE are biased (Imai et al., 2016). Accordingly, the choice between the use of a FE model or a MSM depends on the trade-off between unobserved time-invariant confounding and dynamic causal relationships between diabetes and our outcome variables.[6]

Random effects

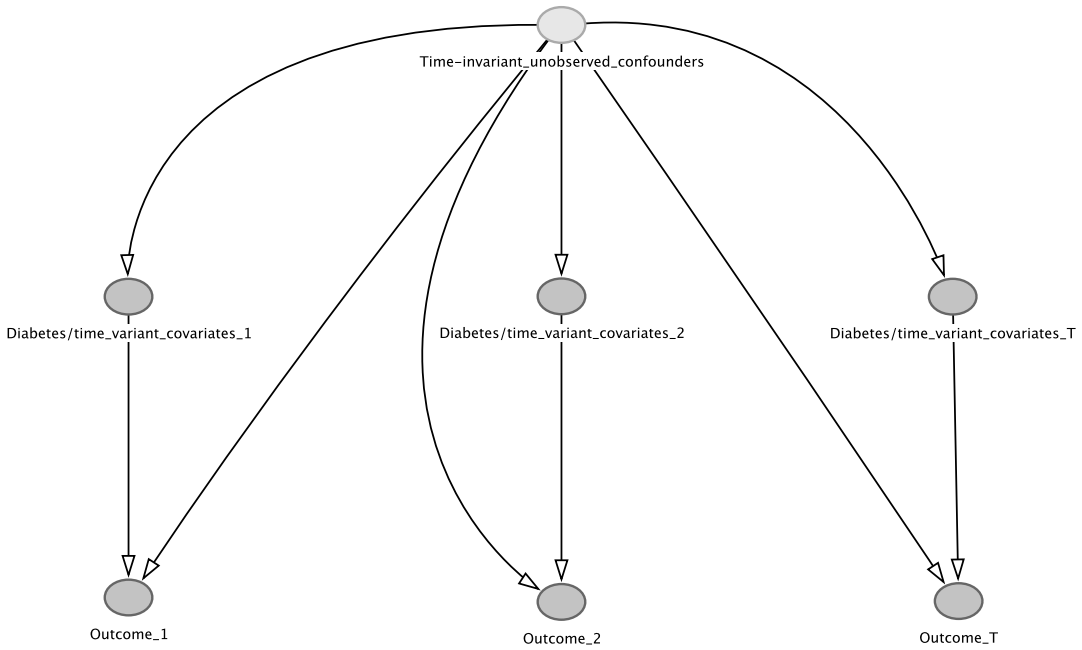
Random effects assume, similar to the MSM, no unmeasured confounding and, similar to the FE model, no dynamic relationship between diabetes and our outcomes. Under these assumptions the RE model is efficient and consistent, making it the preferable estimator if its assumptions are not violated. It is also preferable over the pooled OLS estimator, as the RE estimator takes into account the serial correlation of the errors across time (Wooldridge, 2012).

To discriminate between the RE and FE estimator, a robust Hausman test is carried out using the user written Stata command xtoverid. A rejection of the null hypothesis suggests that the underlying RE assumptions are false and the FE model should be used instead (Wooldridge, 2012).[7]

[6] Because it is not possible to retrieve average marginal effects from a logistic FE model, we prefer to use a linear FE model instead. It generally produces very similar estimates compared to non-linear models (Angrist et al., 2009).

[7] We use the original non-imputed data to carry out the Hausman test.

Figure 9: Direct acyclic graph for the fixed effects model



Notes FE models account for time-invariant unobserved confounding (light grey circle), but still assume the absence of unobserved time-variant confounding. They further do not allow for past outcomes to affect the current treatment, i.e. diabetes status.

Multiple imputation

To avoid excluding participants with missing data on one or more variables, we used chained multiple imputation to impute the missing values in Stata 13 using the user written ICE command (Royston et al., 2009). For most of the included variables, less than 10 percent of the observations were missing. Only the anthropometric measures of BMI and waist circumference had both about thirteen percent missing data which had to be imputed (see Table A17 in the appendix for detailed information on the number of missing observations). In total—before imputation—close to 20 percent of all cases were incomplete, i.e. had at least one variable that had missing data. Thirty imputed data sets were imputed, and the regression results obtained from each set were combined so as to ensure correct standard errors. In each imputed data set the imputed values of each missing variable varies randomly, centred on the value predicted for that record, so as to avoid spurious correlation between the variable and its predictors. When analysing multiply imputed data, increased precision is obtained by using more imputed data sets. Thirty imputed data sets is well above the commonly suggested rule of thumb that the number of imputations should be similar to the percentage of incomplete cases in the data (see for example Bodner (2008) and White et al. (2011) for practical suggestions regarding the optimal number of imputations). Imputation models included all variables used in the MSMs. We imputed missing data in the same wave for which some data were recorded; we did not impute completely missing waves. Further, we assumed that once a diabetes diagnosis was reported, the individual had diabetes in every ensuing wave, even when the observation was missing. If diabetes was never reported in any wave, we assumed that the individual never had diabetes. We then only imputed missing values for those observations that had a non-missing diabetes status. For the calculation of the marginal effects in the MSM logit models, Rubin's rules were applied using the user written Stata command mimrgns (Klein, 2014).

Numbers of observations

Because we used lagged independent variables to construct the stabilized weights for the MSMs, the number of observations used in the MSMs is lower than those used in the FE and RE models, where we do not use lagged variables. The summary statistics shown in Table 23 are based on the observations used in the FE models. The number of observations is stated below each table.

Sensitivity analyses

We conduct three additional sensitivity analyses in order to test the robustness of our results. First, we truncate weights at the 1^{st} and 99^{th} percentile to investigate

the sensitivity of the MSMs to the most extreme weights. While untruncated weights provide unbiased estimates under the assumptions of the MSM, they may not be the most efficient and tend to have larger standard errors (Cole et al., 2008). Second, we estimate the FE and MSMs using the original non-imputed data to ascertain the extent to which multiple imputation affected the results. Third, we report in the appendix the estimates of models using overweight and obesity instead of BMI and waist circumference as the outcomes of interest, to investigate the effect of a diabetes diagnosis on changes in the probabilities to be overweight or obese.

Results

From the descriptive statistics (Table 23), we can observe that people with diabetes in any wave are less likely to be employed. Looking at health behaviours, the prevalence of smoking and drinking is lower for men with diabetes; they also consume fewer calories compared to men without diabetes. Note that it is mainly men who smoke and report alcohol consumption while very few women do so. Further, the diabetes group has both higher BMI and waist circumference levels. They are also older, live in more urbanized areas, are more likely to have insurance and men are somewhat better educated while women are less educated compared to their counterparts without diabetes. Both men and women with diabetes report an average time since diagnosis of around 4.5 years. Looking at per capita household income, men and women with diabetes come from household with higher income levels than those without a diabetes diagnosis. Further, it appears that in China it is less educated women that report a diagnosis, while men with diabetes are better educated compared to those without diabetes.

Predicting the denominator for the stabilized weights (Table 24) we find that for men a higher baseline BMI increases the risk of a diabetes diagnosis. Further, increases in age, waist circumference as well as urbanization levels are associated with higher chances for men to be diagnosed with diabetes throughout the survey. Interestingly, becoming employed decreases the chances of being diagnosed with diabetes slightly, justifying the use of the MSM in our employment models as well. Because these are not causal estimates, it may be that it is more likely for men with a lower risk of diabetes to select into employment.

Table 23: Sample means for males and females, by diabetes status

	Males			Females		
	No diabetes	Diabetes	p-value (t-test)	No diabetes	Diabetes	p-value (t-test)
Employed	82%	68%	<0.001	67%	29%	<0.001
Smokes	58%	47%	<0.001	3%	4%	0.409
Any alcohol consumption	63%	53%	<0.001	9%	4%	<0.001
Daily Kcal eaten (3-day average)	2422	2166	<0.001	2068	1931	0.001
BMI	22.99	24.90	<0.001	23.10	25.80	<0.001
Waist circ. (cm)	82.02	88.81	<0.001	78.80	87.55	<0.001
Age	42.27	52.76	<0.001	43.24	55.32	<0.001
Han ethnicity	87%	89%	0.292	87%	93%	0.002
Rural area	69%	52%	<0.001	68%	51%	<0.001
Married	83%	93%	<0.001	88%	87%	0.392
Secondary education	65%	68%	0.439	50%	43%	0.007
University education	5%	11%	<0.001	4%	1%	0.017
Any health insurance	51%	82%	<0.001	50%	71%	<0.001
Urbanization Index	60.87	74.48	<0.001	61.77	68.68	<0.001
Per capita household income (Yuan (2011))	8617	16328	<0.001	8581	11101	<0.001
Years since diabetes diagnosis	–	4.5	–	–	4.65	–
Observations	23159	284		23369	333	

Higher household income levels are not predictive of a diagnosis for men or women, despite what the descriptive statistics indicated. For women, higher age and waist circumference at baseline, increases in BMI as well as living in a non-rural environment predict a diabetes diagnosis.

The results of our regression analysis are presented in Table 25. Both the MSMs and FE models indicate that women with a diabetes diagnosis have lower probabilities of being employed than their counterparts without diabetes, with a reduction of 11.7 percentage points in the MSM and 11.2 percentage points in the FE model. This translates into a relative reduction in employment probabilities between 16–17%. For men no such effect is observed.

A more ambiguous picture is painted for the effect of a diabetes diagnosis on behavioural risk factor outcomes. According to the MSM, for males a diabetes diagnosis leads to smoking cessation, reductions in alcohol consumption as well as BMI, waist circumference and calorie consumption. Results for women look different. While the point estimates indicate a reduction in all outcomes, these tend to be smaller than those for men and only exhibit strong statistical significance for smoking cessation and alcohol consumptions, factors where women already have a very low prevalence. Compared to the MSM, the FE model finds similar effects for men, apart from a less important effect on smoking cessation. For women, however, it finds much larger, and statistically significant, reductions in BMI and waist circumference compared to the MSM.

The results of the RE models show an even stronger effect of diabetes on female employment probabilities and smaller reductions in male and female BMI and waist circumference, even suggesting a positive association between a diabetes diagnosis and female waist circumference. For the other outcomes, results are very similar to those from the MSMs and FE models. Nonetheless, the Hausman test still rejects the use of the RE model throughout (see Table A24).

Exploring the effect of a diabetes diagnosis over time, we first estimate a specification using time since diagnosis as a continuous variable. The results of the MSMs (Table 26) indicate a steady reduction of female employment probabilities of close to two percentage points per year and of male alcohol consumption, BMI, waist circumference and calorie consumption. The FE model again supports the finding of the MSM, showing very similar, though somewhat larger effects in terms of size and statistical significance. The evidence for changes in risk factors for females is less consistent across models and outcomes, with the MSM suggesting almost no effects while the FE model indicates a reduction in BMI. The effect sizes for changes in health behaviours in women are consistently lower than those found for men.

The RE models again find larger effects on female employment probabilities and a smaller impact of a diabetes diagnosis on reductions in BMI and waist

Table 24: Time variant and invariant predictors of a diabetes diagnosis (denominator of stabilized weights): logistic regression models

	Males		Females	
	(1) β	(2) SE	(3) β	(4) SE
Age (bl)	−.000	0.001	0.004**	0.002
Age squared (bl)	0.000	0.000	−.000**	0.000
BMI (bl)	0.001***	0.000	0.001	0.000
Waist circumference (cm) (bl)	0.000	0.000	0.000*	0.000
3-Day Ave: Energy (kcal) (bl)	−.000	0.000	0.000	0.000
Smoking (bl)	0.001	0.002	0.003	0.006
Alcohol consumption (bl)	0.003*	0.002	0.000	0.005
Urbanization index (bl)	−.000	0.000	−.000	0.000
Secondary educ. (bl)	−.001	0.003	0.003	0.003
University educ. (bl)	−.000	0.006	–	–
Married (bl)	−.002	0.004	−.000	0.004
Any medical insurance (bl)	0.002	0.002	−.000	0.002
Employed (bl)	0.002	0.003	0.001	0.002
Han ethnicity	0.001	0.003	−.002	0.003
Rural	−.001	0.002	−.005***	0.002
Per capita household income (2011 Yuan) (bl)	−.000	0.000	−.000	0.000
Survey year				
2004	0.002	0.002	−.001	0.002
2006	0.003	0.002	−.003	0.003
2009	0.009***	0.003	−.001	0.004
2011	0.001	0.003	0.001	0.004
Age	0.003**	0.001	−.002	0.002
Age squared	−.000**	0.001	0.000	0.000
BMI	−.001	0.000	0.001**	0.000
Waist circumference (cm)	0.000	0.000	−.000	0.000
3-Day Ave: Energy (kcal)	−.000	0.000	−.000	0.000
Smoking	−.003	0.002	0.000	0.006
Alcohol consumption	−.004**	0.002	−.003	0.006
Urbanization index	0.000	0.000	0.000	0.000
Secondary education	0.001	0.003	0.000	0.003
University education	0.001	0.006	–	–
Married	−.000	0.004	−.003	0.004
Any medical insurance	0.001	0.002	−.001	0.002
Employed	−.004**	0.002	−.003	0.002
Per capita household income (2011 Yuan) (2011 Yuan)	0.000	0.000	−.000	0.000

Notes Average marginal effects based on logistic regression. Results for province dummies omitted to preserve space. University education was dropped in the female sample as having university education perfectly predicted diabetes status. N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 25: Analysis of the effect of a diabetes diagnosis on employment status and behavioural outcomes using MSM, FE and RE

	(1) Employment	(2) Smoking	(3) Alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
			Marginal structural model			
Male sample						
Diabetes	−.009	−.070**	−.094***	−.735***	−1.887***	−135.061**
	(.026)	(.032)	(.036)	(.180)	(.574)	(58.593)
Female sample						
Diabetes	−.117***	−.015*	−.029**	−.388	−.335	−45.630
	(.029)	(.008)	(.012)	(.240)	(.631)	(33.530)
			Fixed effects			
Male sample						
Diabetes	0.022	−.023	−.104***	−.715***	−2.217***	−168.297***
	(.030)	(.032)	(.036)	(.183)	(.610)	(62.115)
Female sample						
Diabetes	−.112***	−.027**	−.012	−.644**	−1.251**	−61.175
	(.035)	(.013)	(.010)	(.263)	(.616)	(47.420)
			Random effects			
Male sample						
Diabetes	−.022	−.064**	−.104***	−.379**	−.756	−172.467***
	(.028)	(.029)	(.029)	(.177)	(.542)	(48.768)
Female sample						
Diabetes	−.152***	−.021**	−.019***	−.263	0.459	−39.267
	(.027)	(.011)	(.006)	(.247)	(.570)	(34.256)

Notes The coefficients of the MSM for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. Other control variables for FE/RE: Age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. RE additionally controls for age. MSM controls for baseline values of the same variables as the FE/RE models additionally to baseline values of age, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. Fixed/random effects: N=23443 (male sample), N=23702 (female sample); MSM: N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

circumference for both sexes.

In a second step we estimate a specification using year dummies to capture the potential non-linearity in the relationship between time since diagnosis and our outcomes. The results for the different estimation methods are visualized in Figures 10 and 11 and presented in Tables A19, A20 and A21 in the appendix for the MSM, FE and RE model, respectively. The MSM and FE model indicate a statistically significant reduction in female employment probabilities in the first eight years after diagnosis, with the exception of the fifth and sixth year, where the effects are not statistically significant. Further, male BMI and waist circumference are also reduced significantly in most years, especially using the FE model which finds significant effects in the first six years after diagnosis and then in years nine to twelve. The MSM still indicates reductions but these tend to be of lower statical significance. Calorie consumption is not found to be reduced in a consistent and statistically significant manner, either in the MSM or the FE model. Behavioural risk factors for women are again not found to be reduced consistently, apart from BMI where some trend towards a reduction over time is visible. Interestingly, female employment already decreases rapidly in the first to second year after diagnosis and it does not appear that females are able to increase their employment probabilities later on. Unfortunately, it was not possible to estimate the effects on female smoking status and alcohol consumption due to the low prevalence of these risk factors in females and the lower sample size in the MSM. Using the FE model, all point estimates indicate similar effects. The RE model again suggests larger effects on female employment and lower effects on BMI and waist circumference than both other estimation methods.

The sensitivity analyses using truncated weights shows very similar effects to those using the untruncated weights (Tables A22 and A23 in the appendix), suggesting no important bias and supporting the decision to use untruncated weights. The results using non-imputed data are broadly similar (Tables A24, A25, A26, A27 and A28 in the appendix), in particular for the FE model, and also indicate a reduction in female employment probabilities and male alcohol consumption, BMI and waist circumference. The coefficients of the MSM still point into the same direction as those using the imputed data, but the estimated effects are smaller in size and confidence intervals are relatively large. The RE model still shows a stronger effect on female employment probabilities and smaller reductions in especially the weight measures BMI and waist circumference. Using overweight and obesity instead of BMI and waist circumference as indicators for weight changes, we do not find as consistent reductions in weight status for men as we did using the continuous estimates (Tables A29 and A30 and Figure A1 in the appendix). Nonetheless, the point estimates still show a reduction in obesity, in particular over time and for men, supporting the reductions found

Table 26: Analysis of the effect of each year since diabetes diagnosis on employment status and behavioural outcomes using MSM, FE and RE

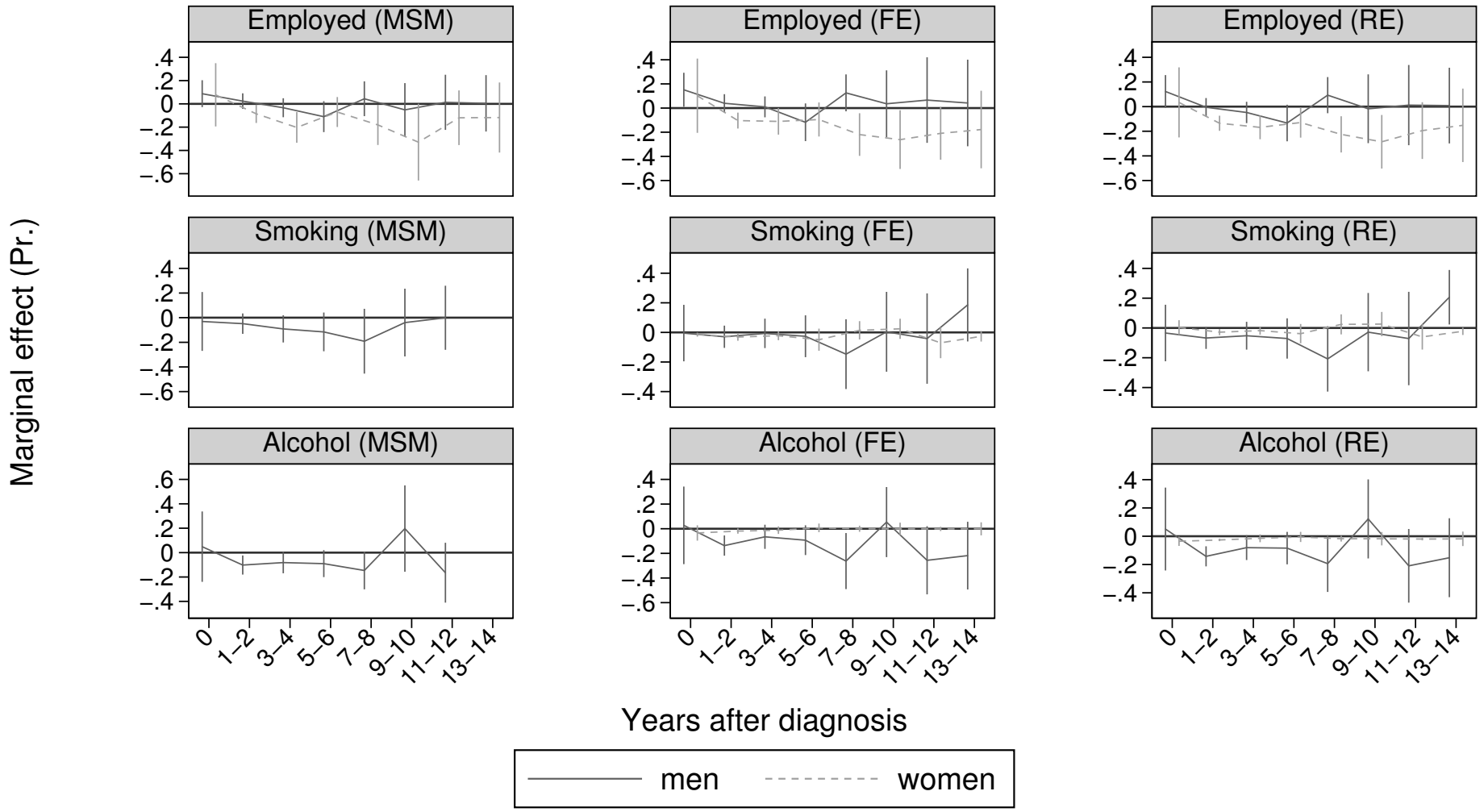
	Employment	Smoking	Any alcohol	BMI	Waist (cm)	Calories (kcal)
			Marginal structural model			
Male sample						
Time since diagnosis	−.003	−.010*	−.014**	−.127***	−.340***	−21.770**
	(.004)	(.005)	(.007)	(.031)	(.099)	(9.842)
Female sample						
Time since diagnosis	−.017***	−.002	−.004	−.066*	−.072	−8.735
	(.005)	(.001)	(.003)	(.040)	(.109)	(5.589)
			Fixed effects			
Male sample						
Time since diagnosis	−.001	−.003	−.017**	−.150***	−.520***	−22.286**
	(.007)	(.006)	(.007)	(.037)	(.121)	(11.083)
Female sample						
Time since diagnosis	−.019***	−.003	−.000	−.102***	−.215*	−6.747
	(.007)	(.002)	(.001)	(.039)	(.117)	(7.028)
			Random effects			
Male sample						
Diabetes	−.006	−.009*	−.015***	−.099***	−.269***	−24.703***
	(.006)	(.006)	(.005)	(.035)	(.096)	(8.655)
Female sample						
Diabetes	−.023***	−.002	−.002**	−.056	0.013	−6.444
	(.006)	(.002)	(.001)	(.039)	(.114)	(5.670)

Notes The coefficients of the MSM for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Other control variables for FE/RE: Age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. RE additionally controls for age. MSM controls for baseline values of the same variables as the FE/RE models additionally to baseline values of age, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. FE/RE: N=23443 (male sample), N=23702 (female sample); MSM: N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

using continuous measurements.[8]

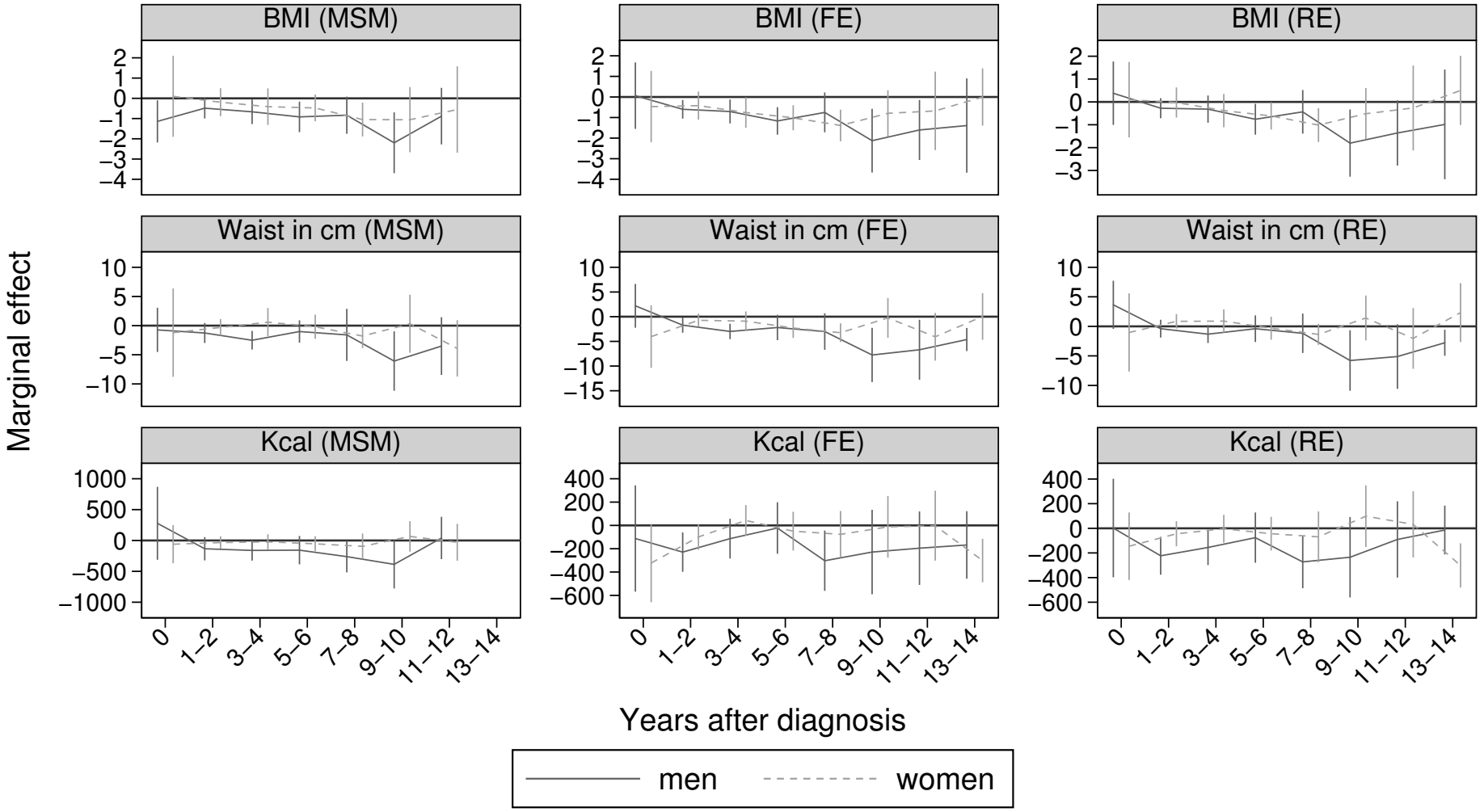
[8]The coefficients for overweight are difficult to interpret as it is unclear if the negative coefficient is caused by people transferring into obesity or into normal weight.

Figure 10: The effect of time since diabetes diagnosis on employment, smoking and alcohol consumption (duration groups)



Note The visualized coefficients are based on the results of the regression models shown in Tables A19 and A20 in the appendix. 95% confidence intervals.

Figure 11: The effect of time since diabetes diagnosis on BMI, waist circumference and calorie consumption (duration groups)



Note The visualized coefficients are based on the results of the regression models shown in Tables A19 and A20 in the appendix. 95% confidence intervals.

Discussion

The evidence for the impact of a diabetes diagnosis on employment probabilities and behavioural risk factors remains scarce, in particular in MICs, where diabetes has become a major contributor to the burden of disease. We added to this evidence by exploring these relationships using longitudinal data from China, also improving upon previously used methodologies by taking into account the potential relationship over time between diabetes and these outcomes.

Our results suggest that receiving a diabetes diagnosis in China leads to a strong and lasting reduction in female, but not male, employment probabilities. We also found reductions in male BMI and waist circumference, alcohol and calorie consumption and potentially smoking to be associated with a diabetes diagnosis. We did not, however, find similar changes in behavioural risk factors for women. Accordingly, it appears that women in China have to endure stronger adverse labour market effects of diabetes and at the same time are less successful then men at making risk behaviour changes to reduce their risk of diabetes complications.

The MSMs and FE models indicated very similar results suggesting that they are robust and that time-invariant confounding factors may play a limited role over and above baseline and time varying confounding factors. The MSM results suggest that in particular BMI and waist circumference levels as well as employment status can cause selection into a diabetes diagnosis and are then later themselves affected by the diagnosis, justifying the use of a MSM. The RE models further indicate that insufficiently accounting for confounding can—at least in this setting—lead to an overestimation of the impact of diabetes on employment status and an underestimation of the effects of a diagnosis on weight measures (BMI and waist circumference). However, confounding may only be of limited relevance for alcohol consumption, where the RE models showed very similar results.

Limitations

The study has several limitations. While we used two estimation methods to reduce the influence of observed and unobserved confounding, respectively, none of the models is able to account for both forms of confounding. Therefore a causal interpretation is only possible under restrictive assumptions, namely no unobserved time-variant confounding for the FE model and positivity, exchangeability and consistency for the MSM. The assumption of positivity is likely to hold, given that every person should have at least a small chance of receiving a diabetes diagnosis. This is also supported by the relatively small range of stabilized weights and absence of zero-weights. The assumption of exchangeability or

no unmeasured confounding could potentially be violated if not all time-invariant and time-variant confounders were accounted for, but this cannot be known for certain from existing data. We tested for part of this assumption by estimating a FE model and, given that the results remained very similar, this suggests that unobserved time-invariant confounding may be of limited relevance in this case, even though this remains speculative as the Hausman test indicated some time-invariant confounding. Consistency would have been violated if a diabetes diagnosis had been reported but the person had actually not been diagnosed with diabetes. This was likely only violated in very rare cases of misreporting, given that specificity of diabetes self-report is very high in China (Yuan et al., 2015). Because we were interested in the effect of a diabetes diagnosis, unobserved diabetes did not violate the consistency assumption.

A limitation of the FE model is the possibility of time-variant confounding due to prior outcomes (for example employment status) affecting the current treatment (a diabetes diagnosis). We found some evidence that prior outcomes could affect selection into a diabetes diagnosis, potentially introducing bias in our FE estimates. Given that the FE estimates were close to those of the MSMs, it could be that this bias may not have been very strong. Overall, it remains difficult to pin down the potential source of a potential bias as, for example in the female employment models, both the MSM and the FE results are very similar while the RE results indicate a somewhat bigger adverse effect. We have some evidence for both models that their underlying assumptions may not hold, with the Hausman test suggesting time-invariant confounding and the results of Table 24 indicating some time-variant confounding due to prior outcomes.

Finally, a limitation is that in this study we only observe the combined effect of all that entails a diabetes diagnosis. However, a diabetes diagnosis can entail a variety of 'treatments' that are difficult to disentangle and may each have a distinct effect on the explored outcomes.

Potential mechanisms

The effects of diabetes on employment and behaviour could work through several mechanisms. Firstly, the provision of information at diagnosis may causes increases in stress and anxiety, but could also reduce anxiety by providing an explanation for the experienced symptoms (Peel et al., 2004), with both potentially affecting productivity. Secondly, a diagnosis is also the starting point for medical treatment, which could help to alleviate symptoms and to lose weight, but also poses new challenges, in particular if treatment entails the exogenous provision of insulin or adherence to strict meal plans, likely adding to the burden of diabetes in daily life (Pibernik-Okanović et al., 1996; Vijan et al., 2005). Thirdly, ad-

herence to medical treatment may be heterogeneous across people with diabetes, with non-adherence likely leading to a further worsening of risk factors for complications, while good adherence may prevent or delay debilitating complications (Asche et al., 2011). Fourthly, a diagnosis may also cause lifestyle changes such as increasing exercise levels, eating healthier and reducing smoking or alcohol consumption, all potentially affecting the risk of developing further complications and of changes in productivity. In the current study, it is not possible to ascertain the role of each of these factors in affecting employment probabilities and behavioural risk factors. Only for the reductions in smoking and alcohol consumption, it seems reasonable to attribute them to diagnosis induced awareness of the need to reduce these risk factors, as other pathways appear less likely to be relevant.

The found adverse effect of diabetes on employment is in line with other studies on the labour market impact of diabetes that have found diabetes to reduce employment probabilities for women (Harris, 2009; Latif, 2009; Minor, 2011; Seuring et al., 2016)—often more than for men. Most comparable to our results are likely the results from Mexico in Chapter 4, which were also based on FE estimations and data for a similar time period (Seuring et al., 2016). The study found significant reductions for both males and females of about 5 percentage points. Taking into account the lower overall employment rate of Mexican women compared to men, this translated into a 16% reduction in female employment probabilities, a figure comparable to the effect on Chinese women. However, in Mexico also men experienced adverse effects, unlike to what we found for China.

The effects on behavioural risk factors can be compared to the study by Slade (2012). Slade finds reductions in alcohol consumption and smoking, though it appears that these reductions were not maintained over a longer time period. Unfortunately, Slade only provided information for the entire sample and the male sample, so that we cannot compare them directly with our results for women. In terms of the effect on weight, again both studies cannot be directly compared because Slade investigated the effect of a diagnosis on being overweight or obese, while we used continuous weight measures in our primary analysis due to the discussed difficulties of defining cut-off values for Asian populations. Slade found an initial reduction in weight status, but also that people with diabetes tended to become more likely to be overweight or obese after some time. Our results using overweight and obesity could tentatively be interpreted to indicate a more constant reduction in obesity over time, suggesting that reductions in weight in Chinese men may be longer lived than in the USA. Importantly—and in concordance with our findings—he found that simple covariate adjustment led to biased estimates of the impact on weight status, finding a positive relationship. This underlines the importance of accounting for potential sources of confounding.

The permanent reduction in male BMI and waist circumference we have found has also been observed in a cohort of Danish patients (De Fine Olivarius et al., 2015), where weight increased in the years preceding diagnosis, while after diagnosis weight decreased. The exact reasons for this decrease were unknown. De Fine Olivarius et al. (2015) attributed them to motivation changes as a result of the diagnosis, concluding that the time around the diagnosis may represent a window of opportunity to obtain long lasting weight change. Nonetheless, reductions in weight may also be the result of treatment initiation with metformin or other diabetes drugs that have been shown to lead to weight reductions (Yang et al., 2014). Importantly, in the present study the reduction in male BMI levels and waist circumference were accompanied by reduced energy intake, suggesting that the changes in weight were at least partly the result of lower energy intake. Further, given that in China diabetes incidence has been especially attributed to a high accumulation of visceral fat and central obesity (Ma et al., 2014), the reductions in waist circumference may have had a particular positive effect on diabetes control and the prevention of comorbidities. Together, the lower levels of energy intake and waist circumference after the diagnosis allow for the interpretation that the reductions in BMI were due to fat loss and not lower lean body mass (Klein et al., 2007).

For women, however, we did not find similar strong evidence for reductions in BMI, waist circumference or energy intake. The relatively smaller effects for women could indicate a lower ability to change behaviours supportive of weight loss. This appears to be supported by the smaller reductions in energy intake. This could have—at least partly—contributed to a higher risk for diabetes complications further down the line, also adversely affecting employment probabilities. Apart from this, other explanations for the lower weight loss and larger employment penalty for women compared to men include their lower educational attainment, which has been indicated as a factor in preventing better glucose control (Luo et al., 2015) and may also affect the ability to successfully change behaviours. Lower income levels for females compared to men may also have negatively affected the ability to receive adequate treatment following a diagnosis, limiting their ability to change health behaviours (Luo et al., 2015), increasing the risk of complications. We found that women with diabetes lived in households with lower income levels compared to men with diabetes, however, these income levels were still higher then for those without diabetes. Nonetheless, it may still be the case that women were less likely to access care due these differences in income. Moreover, there are likely biological factors that lead to worse health outcomes for women compared to men. There is some evidence that, due to different ways of fat storage between men and women, men tend to cross the diabetes threshold at an earlier point in time and at a comparatively healthier

metabolic state then women (Peters et al., 2015, 2014a,b). Women are more likely to have spend more time in a pre-diabetes state (Bertram et al., 2010) and to cross the threshold only once their metabolic health has significantly deteriorated, leading to a greater risk of cardiovascular disease and stroke (Peters et al., 2015). Supporting this, a study for China found a greater prevalence of diabetes comorbidities in Chinese women compared to men (Liu et al., 2010). In this light it may not be surprising that we find more conclusive evidence of worsening employment probabilities for women. If women are less likely to receive proper treatment and to change their health behaviours and at the same time have a greater risk for complications than men, the long term effects of diabetes on their health are likely more severe than for men and consequently affect their employment status to a greater extent.

Taken together, the results suggest a lower risk of unemployment for men with diabetes potentially due to their greater ability to reduce behavioural risk factors, while the effect of diabetes on employment for women is substantial potentially because no such changes in behaviour take place. Further analysis is needed to test this formally and is beyond the scope of this paper.

Conclusion

Our results indicate worse outcomes for women then men after a diabetes diagnosis, with women experiencing a reduction in employment probabilities accompanied by and potentially partly due to an inability to reduce important risk factors for diabetes complications. For males, the opposite pattern is found as they do not experience adverse employment effects and are able to achieve reductions in the investigated risk factors. These findings are robust to the application of two distinct, but complementary econometric techniques. Overall, given the large prevalence of undiagnosed diabetes, our results indicate that an early diagnosis may be a good way to foster early behaviour change that could lead to more positive health and economic outcomes for people with diabetes over time. It appears, however, that greater emphasis needs to be put on reducing the burden of diabetes for women to reduce the observed inequities in the impact of diabetes. Future research should try to unravel the mechanisms behind these differential outcomes for men and women, investigating more formally whether differences in behavioural risk factors could be a potential explanation.

6 Discussion and conclusions

Chapter overview

Diabetes has reached epidemic proportions in middle-income countries (MICs) and is a major contributing factor to poor health and early mortality, as also discussed in Chapter 1. The economic impact of diabetes on individuals and healthcare systems has, however, received limited attention. In particular, we have a limited understanding of the effect of diabetes on individual labour market outcomes. Moreover, little is known about how people with diabetes currently achieve positive change in behaviour risk factors to prevent the disabling complications of diabetes, and whether this plays a role in the effect if the disease on labour market outcomes. The main goal of this thesis has been to assess the economic burden of diabetes in MICs, focusing on two predominant and large countries with an increasing diabetes disease burden. This should help to better understand the importance of primary and secondary prevention of diabetes and to identify those populations most susceptible to the adverse economic effects of diabetes.

Four separate studies were conducted that intended to answer the research questions posed in Chapter 1. This concluding chapter has four parts. Firstly, it summarises the principal findings. Secondly, it contextualises the findings within the wider literature and provides implications for policies. Thirdly it reflects on the methods. Finally, there are suggestions for future research and concluding comments.

Summary of principal findings

Chapter 2 set out to provide an overview of and critically assess existing studies on the economic costs of type 2 diabetes globally. This not only included cost-of-illness (COI) studies but also studies on labour market outcomes. Systematic review methods were used and the evidence was synthesized narratively. 86 COI studies and 23 labour market studies were identified. Of those, 24 came from low- and middle-income countries (LMICs), with 23 being COI studies.

For COI studies, the review found a large range of estimated costs, with the largest per-capita costs being observed in the USA while costs were generally lower in LMICs. However, in LMICs treatment costs were paid almost entirely out-of-pocket by the poor due to a lack of health insurance coverage, consuming considerable parts of their annual income. The review also found considerable differences in the used methodologies and in the study quality. This made it difficult to directly compare the results across studies. While in many high-income country (HIC) studies an incremental costing approach was used and data sources were representative for a distinct population, studies in developing countries often

had to rely on non-representative, relatively small convenience samples, often lacking a control group. Many studies also lacked explicit mentioning of the study perspective or of the costing components that were included.

For labour market impact studies, most found adverse effects of self-reported diabetes on employment probabilities, wages or working days. Studies were concentrated on a few HICs, in particular the USA. More recent studies took into account potential biases due to the endogeneity of diabetes, mainly using an instrumental variable (IV) strategy with the family history of diabetes as an instrument. However, the direction of bias was ambiguous across different studies and countries.

The review also identified methodological and thematic areas that previous research had only covered sparingly. No COI study took into account the possibility of biased estimates as a result of the endogeneity of diabetes. Consequently, there is a lack of evidence in the literature about the potential bias in the cost estimates of diabetes COI studies. Further, few studies used an incidence approach to investigate lifetime costs of people with diabetes, which could provide better information about the dynamics of cost increases post diabetes diagnosis.

Despite these identified limitations of the COI literature, the review provided a picture of the healthcare costs of diabetes in almost every continent. This was not the case for labour market studies, where almost no evidence was found for LMICs. There is reason to expect the labour market impact of diabetes to be very different in LMICs compared to HICs, given the LMICs' less advanced healthcare systems, later diagnosis but—in some populations—earlier onset of diabetes and greater susceptibility to develop it, the larger informal labour market and overall different labour market structure in LMICs. Also, in terms of methodology, studies had not taken advantage of panel data techniques to get closer to a causal interpretation of their estimates. Especially studies on the effect on employment probabilities had instead relied on the same—at least debatable—identification strategy using IVs. Therefore, a study using a different identification strategy was warranted.

Importantly, no study investigating the impact of undiagnosed diabetes on labour market outcomes was identified by the review. Hence, an important part of the population with diabetes had been mostly neglected. This left open the question in how far results for self-reported diabetes were applicable to the part of the population that was unaware of its diabetes status.

Based on the findings of the review, the three research studies that followed addressed parts of the identified gaps, in particular focusing on labour market outcomes.

Chapter 3 provided the first evidence for the impact of diabetes on employment probabilities in a developing country, where diabetes had become a public health concern. Because little was known about the equity impacts of diabetes, a further goal was to investigate the heterogeneity of effects across formal and informal employment and for the 'rich' and 'poor'. Due to the unavailability of an alternative identification strategy, the study applied the already established IV approach using parental diabetes as the instrument. Using further background information on parental education, it improved upon earlier studies by controlling for a potential confounding pathway that could have invalidated the specific instrument. It further used two methods to implement the IV approach. The main analysis was based on a bivariate probit model that had been shown to be better suited for our specific data, in comparison to a standard linear IV model. We nonetheless also provided the results of the latter approach. Both models found no indication of diabetes being exogenous in this context so that a simple univariate probit model was used for inference. The results showed an adverse effect of diabetes on employment probabilities in Mexico of about 10 percentage points for men and 5 percentage points for women. The subgroup analysis suggested that the adverse employment effects impacted mainly those above age 44, while younger people seemed less affected. Also, being poorer increased the exposure to negative employment effects of diabetes. The same was the case for those in the informal compared to those in the formal labour market. Across all models, the point estimates were bigger for males than for females.

Chapter 4 went on to address several questions identified in Chapter 2 that had not been investigated in the first Mexico study. Further, the robustness of the findings of Chapter 3 had to be tested using more extensive and recent data and a different identification strategy. Chapter 4 thereby took advantage of a recent extension to the data used in Chapter 3. The data now spanned three waves and eight years, which allowed for the use of a longitudinal individual fixed effects (FE) model to estimate the relationship of self-reported diabetes with employment. Additionally, the investigated labour market outcomes were extended to wages and working hours. Also, it was now possible to investigate the relationship of diabetes duration with labour market outcomes, in order to better understand the timing of any diabetes impact on labour market outcomes. Importantly, the additional wave also provided information on diabetes biomarkers to separately explore the effects of diabetes for the entire population with diabetes as well as those unaware of diabetes.

The analysis carried out in Chapter 4 confirmed the adverse relationship of self-reported diabetes with employment, finding a 5 percentage point reduction for males and females alike. Given the relatively low female employment rate, this

translated into a 14% relative decrease in employment probabilities for women compared to 6% for men. Compared to the cross-sectional results of Chapter 3, the estimated effects of the FE model are about half the size for men, but are similar and of stronger statistical significance for women. This is likely due to the additional data used in Chapter 4, but could also partly be the result of the different estimation technique. For wages and working hours no adverse effects of self-reported diabetes were found.

Further analysis showed that the most adverse effects were concentrated among self-employed and independent agricultural workers, potentially due to lower job security and access to healthcare in these often informal jobs. Further, Chapter 4 revealed that the adverse effect of diabetes on employment appeared shortly after diagnosis, then levelled off for some time until it appeared again. This pattern was observed for both males and females, albeit only statistically significant for the former. Interestingly, it was found that when the employment effects levelled off, wages started to fall, again for both genders. This suggested that during this period diabetes, plausibly through reductions in productivity, mainly reduced wages, without affecting job loss.

Finally, the results of the biomarker analysis presented in Chapter 4 showed that relying on self-reported diabetes information can lead to measurement bias in the coefficient of diabetes. Using the biomarker data to identify people with diabetes, smaller effects especially on employment probabilities were found compared to self-reported diabetes, caused by the non-existent associations between undiagnosed diabetes and employment probabilities. It was further found that part of the difference in effects between self-reported and undiagnosed diabetes could be explained by differences in subjective health status, with those self-reporting diabetes also reporting a worse health status. Interestingly, differences in glycated hemoglobin (HbA1c) levels did not drive the stronger effects for those self-reporting.

Chapter 5 continued the investigation of the impact of self-reported diabetes on employment probabilities, but this time in China. It further investigated how a diabetes diagnosis affected diabetes-relevant health behaviours in a developing country. Because the relationships may be biased due to confounders not previously taken into account, the study used two different econometric strategies: marginal structural models (MSMs) and FE. Each controlled for a different source of confounding, improving the robustness of the identified effects. The used data consisted of six waves of the China Health and Nutrition Survey (CHNS), covering a period from 1997 to 2011.

The results from Chapter 5 provided further evidence of a deterioration of employment probabilities after a diabetes diagnosis, though this time only for

women. They experienced a reduction in employment probabilities between 11 to 12 percentage points. For men, the MSM and FE models showed insignificant relationships. These reductions for women were similar to those found in Mexico (16–17% in China and 14% in Mexico) when the female employment rates in both countries were taken into account. The results for behavioural risk factors also suggested different effects for men and women. According to the results, men were able to reduce their alcohol consumption, body mass index (BMI) levels, waist circumference and daily calorie consumption, potentially reducing the risk for diabetes complications (Wilding, 2014). For women, no strong evidence for similar reductions was found. A similar picture remained when investigating the effects over time using linear and non-linear specifications. On the one hand they suggested maintained reductions in female employment probabilities over time but no strong changes in risk factors. On the other hand, men were able to more consistently reduce behavioural risk factors in the years following diagnosis while not experiencing any labour market penalties. Overall, the findings suggested a potential relationship of changes in risk factors with changes in labour market outcomes.

Implications for policy making

The findings of this thesis indicate an important global economic burden of diabetes and have added first evidence on the effect of diabetes on labour market outcomes in MICs. The thesis also showed that diabetes—at least as far as labour market outcomes are concerned—did not similarly affect the population unaware of their diabetes diagnosis as it did those who were aware. Additionally it showed, that a diabetes diagnosis can elicit positive changes in behavioural risk factors, though to different degrees for men and women. Further, the distributional analysis brought to light that the burden of diabetes appears to be distributed unequally, disproportionally affecting the poor, those in the informal labour market and women.

These findings may lead to several implications to reduce the economic burden of diabetes in MICs.

Inequities in the economic burden of diabetes

An important finding of this thesis are the economic inequities in the burden of diabetes. In Chapter 2, the review found a high out-of-pocket (OOP) burden in LMICs, especially for those with no insurance coverage. Chapter 3 showed that the adverse employment effects were concentrated among those in the informal labour market and with fewer resources. This was further supported by

findings from Chapter 4 that indicated a greater reduction in the probabilities to work in the agricultural or self-employed sector, while for those working in a non-independent wage job—that often entails greater contractual job security and better access to health insurance—diabetes did not appear to elicit negative effects. Chapter 5 found bigger adverse employment effects and more modestly positive behavioural changes in women compared to men after they had received a diabetes diagnosis. These gender inequities are also supported by the results for Mexico, in particular by Chapter 4, where, taking into account the lower overall employment rates for women in Mexico, the relative reduction in employment probabilities was much greater for females than for males.

There may be several potential strategies how to reduce these inequalities. In particular, these include tackling the observed differences by gender, better prevention of diabetes, earlier diagnosis and better treatment of those diagnosed.

Gender

One of the main results of this thesis is the identification of women with diabetes as a specific target group. Gender differences in the disease burden of diabetes have come to the forefront only recently (Peters et al., 2015), but may hold one of the keys to reducing the economic burden of diabetes. In particular, it appears that biological differences between men and women likely lead to greater adverse effects of diabetes compared to men (Bertram et al., 2010; Peters et al., 2015, 2014a,b) which could be driving the observed differences in the economic effects. Efforts to reduce the burden for females would include increasing awareness among doctors about the higher risks for women to develop diabetes complications, as well as screening for cardiovascular risk factors in women at or before a diabetes diagnosis. This would present an opportunity to prevent a further escalation of the cardiovascular risk profile (Peters et al., 2015). Additionally, weight reduction seems to be the single most important step to reduce the risk of diabetes and ensuing complications in women (Peters et al., 2015). As this thesis has shown, women in China were not able to achieve weight reductions to the extent men did and therefore may need to be treated differently. Future work on LMICs can provide important contributions to help develop effective strategies to obtain this type of improvements in women's health outcomes.

Moreover, reductions in socioeconomic inequities identified in this thesis may also contribute to a reduction in the observed gender differences. If women have fewer economic resources than men, are more likely to work in the informal labour market and less likely to be insured (Galli et al., 2008) and therefore are more adversely affected by diabetes, then interventions targeting the poor and uninsured should specifically help women. Some of these interventions will be discussed

below.

Prevention

Greater prevention of diabetes could help to reduce the observed inequities and the individual economic burden of diabetes. Given the inequities found in this thesis, such efforts may be particularly worthwhile if they focus on those disproportionally affected by the adverse economic effects of diabetes.

One option is the introduction of national policies to affect food consumption. There is already some real life evidence of such interventions with the goal of reducing obesity in developing countries. In Mexico, a 10% tax on purchases of sugar-sweetened beverages and 'junk food' has been introduced in 2014. First results have suggested a reduction in purchases of these goods after the introduction of the tax, with a steeper decline for those with lower income levels (Batis et al., 2016; Colchero et al., 2016). If these changes in consumption actually lead to a healthier diet and are large enough to cause reductions in obesity and diabetes prevalence has not been evaluated yet and remains to be seen. Other efforts to prevent diabetes in LMICs include increasing the awareness of diabetes and how to prevent it via population level campaigns, and increasing the accessibility to sport courses and fitness equipment to foster physical activity (Cefalu et al., 2016).

Another option is the identification of at risk groups and targeting them with interventions to increase physical activity and dietary changes. These have shown promising results across the globe, including in developing countries such as India and China, where interventions have caused long term reductions in the risk of developing diabetes (Cefalu et al., 2016). For example, for China a randomized controlled trial provided long term lifestyle interventions to reduce the incidence of diabetes and cardiovascular disease as well as to reduce mortality in people at risk of developing type 2 diabetes. Over the active trial period of six years, the diet and exercise intervention reduced the relative risk for diabetes incidence by over 50% (Pan et al., 1997). A more recent evaluation of the long-term impact of the interventions showed that over 20 years after the intervention had ended, the incidence of diabetes was still over 40% lower in the intervention group. Further, people that had received the intervention spend 3.6 years less with diabetes than those in the control group (Li et al., 2008). However, the translation of these interventions to real-world settings has been less successful, even in high-income countries (Kahn et al., 2014; Wareham et al., 2016). For example, weight loss has only been a small fraction of the reductions achieved in trials, likely often too little to prevent diabetes. Kahn et al. (2014) argue that weight loss is notoriously difficult to maintain over a longer period of time, with trials often only

capturing initial weight loss, but not the return to previous weight levels over time. Therefore, prevention efforts based on lifestyle interventions or aiming at weight loss may not yet be translatable into real life, as too little is known about their cost-effectiveness and long-term effects to justify the use of limited resources (Kahn et al., 2014). There are also questions about the cost-effectiveness of these interventions if scaled to a population level and the challenge of finding qualified staff to implement lifestyle interventions at the local level.

The evidence for pharmacological interventions mainly using metformin also indicates a reduction in the risk of diabetes. However, Cefalu et al. (2016) mention the potentially large heterogeneity in the benefit of pharmacological interventions across ethnicities. More research on this subject will be needed to find out if successful pharmacological interventions in one ethnicity can be translated to other ethnicities. Nonetheless, Cefalu et al. (2016) argue that preventive metformin treatment—which has been shown to reduce diabetes incidence in a number of randomized controlled trials—in individuals with a high risk of progressing to diabetes may be the best approach in countries with few economic resources. Low-cost generic versions of metformin exist, are considered essential diabetes medications in almost all LMICs (Bazargani et al., 2014), are effective in preventing or delaying the onset of diabetes, and are safe (Rojas et al., 2013). They therefore may present a relatively cost-effective intervention that could be applied using existent healthcare infrastructure and pharmacies. It could be especially effective in MICs, where the healthcare system infrastructure is much more developed than in low-income countries (LICs). Nonetheless, specific targeting of populations most likely to benefit from pharmacological preventative treatment will be needed, as the effects of metformin appear to be heterogeneous across age. Further, pharmacological treatments may also exhibit different effects across populations and ethnicities (Cefalu et al., 2016).

The identification of high-risk individuals that could be targeted with the mentioned interventions may pose an additional hurdle to successfully preventing diabetes. Population level screening could be a way to identify people at risk. Screening could also be carried out at the workplace or the community, and existing medical records could be used to identify people at an increased risk. Further, there may be possibilities to promote risk self-assessments using online resources through advertising and social media (Cefalu et al., 2016). However, scientific evidence of the cost-effectiveness and feasibility of screening for high-risk individuals in LMICs is non-existent, and if it were to happen may overwhelm healthcare systems. It also carries the risk of further widening health inequities if the lower income populations are less likely to attend screening efforts (Wareham et al., 2016).

Diagnosis

If prevention is not successful and people have developed diabetes, the earlier diagnosis of diabetes to prevent further complications could be a viable option to reduce the economic burden of diabetes. In Chapter 4, adverse labour market outcomes were only observed for the self-reporting population with diabetes, suggesting that the adverse impact manifested only after some time of living with the disease and mainly after diagnosis. This is not surprising given the gradual increase in blood glucose as diabetes progresses and the concomitant relatively slow deterioration of health (Bertram et al., 2010). While earlier detection of diabetes via screening did not yield important improvements in disease outcomes in the Addition-Trial in European HICs, this might be markedly different in MICs. The large undiagnosed population found in Mexico in Chapter 4 as well as for other LMICs in a recent study by Beagley et al. (2014), suggests that, compared to HICs, in MICs more people with diabetes remain undiagnosed for an extended period of time. Therefore, earlier detection may have a greater beneficial effect (Choukem et al., 2013), in particular, if it can prevent complications from appearing within a person's productive lifespan.

The results of Chapter 5 indicate that a diagnosis can introduce positive changes in behavioural risk-factors that may be directly related to a reduced economic burden of diabetes, suggesting that diagnosing those currently unaware could have positive effects. Nonetheless, earlier detection would also increase healthcare demands and costs, at least in the short term. Therefore, evidence is needed that explores the trade-off between the costs generated by longer treatment periods and a greater number of patients due to an earlier diagnosis and potential reductions in healthcare expenditures and productivity losses as a result of lower complication rates at later stages (Engelgau et al., 2012). Evidence on the cost-effectiveness of a population-based diabetes screening program was provided by a recent study from Brazil, where over 22 million people over the age of 40 were screened for diabetes, being the first trial evaluating an actual real-life population-based diabetes screening program in a developing country (Toscano et al., 2015). It was unclear if the program could be considered good value for the healthcare system, as the cost-effectiveness of the findings depended strongly on the underlying assumptions about how effective treatment would be in preventing coronary heart disease and stroke. Given the results from this thesis, cost-effectiveness might be greater from a societal perspective if an earlier diagnosis would prevent or decrease losses in productivity and productive lifespan. Of course, early diagnosis may only be reasonable if the healthcare system is sufficiently developed to allow all diagnosed cases access to appropriate treatment options (Engelgau et al., 2012; Toscano et al., 2015).

Apart from worse health in the population aware of its diabetes, another policy relevant reason for the difference in the observed effects could be the psychological effect of a diabetes diagnosis. Reductions in productivity may be the result of increasing anxiety and depression as a result of becoming aware of the disease and its potential consequences. Further, difficulties in adapting to the treatment regime may cause additional stress. As discussed in Chapter 4, there is some evidence that becoming aware of the disease leads to reductions in labour income likely due to its psychological effects (Liu et al., 2014). If this is confirmed by other studies, then strategies to provide better guidance and support at diagnosis and thereafter to reduce the psychological burden of the disease could be worthwhile.

Treatment

Earlier diagnosis, however, will only be worthwhile if those diagnosed are able to receive effective diabetes treatment. The adverse labour market effects found for those with self-reported diabetes, and the increase in effect size over time after diagnosis, suggest that currently this may not be the case and adverse health and ensuing economic events often cannot be prevented. This may have several reasons. The diagnosis could happen too late to prevent first complications from having developed, making it increasingly difficult to prevent further complications. Another reason could be the sub-optimal treatment of the disease, in particular in the most adversely affected—likely socioeconomically disadvantaged—groups identified in this thesis.

Therefore, an important step to improve outcomes would be the provision of better quality in diabetes treatment, targeting the identified groups and tailoring interventions according to their socioeconomic, physical and personal characteristics (Cefalu et al., 2016). The existing evidence on diabetes treatment models applicable in very resource constrained settings has recently been reviewed by Esterson et al. (2014). While the evidence is still limited, the study provided information on interventions that have had some success in improving diabetes treatment for the poor. Further, it identified common characteristics of these successful interventions: collaboration, education, standardization of guidelines and algorithms, technological innovations, and resource optimization. The authors recommended that initiatives to provide care to underserved populations should be built on collaborations between academic institutions, hospitals, the private sector and other organizations such as local governments. This should help to achieve goals that would otherwise be difficult to reach for one stakeholder alone. Further, programs should aim at providing appropriate education to doctors to increase their ability to successfully treat people with diabetes. For very remote communities, Esterson et al. (2014) suggested the use of peer-support programs,

so that a few well educated community members or nurses could help their peers with the challenges of diabetes management. Further, a need for standardized guidelines and treatment algorithms was identified as a means for healthcare professionals to improve and maintain their standards of care. Given that mobile phones have already reached even very remote areas and are common in the developing world, interventions based on existent technologies could also improve care and diabetes outcomes. They could facilitate communication between doctors and their patients as well as tracking and controlling diabetes management and outcome measures. Finally, resource optimization to use available and constrained resources more effectively, e.g. by transferring certain responsibilities from doctors to nurses or from healthcare professionals to peers, could be an option in very resource constrained settings (Esterson et al., 2014). Together, the presented strategies could help in reaching and treating poorer parts of the population.

A number of interventions have been implemented in LMICs to improve care for people with diabetes. Focusing on China, Mexico and other MICs, some of these will be mentioned here. Most of these interventions apply at least one of the recommendations mentioned in the previous paragraph. For Mexico, a recent randomized controlled trial tested the effects of providing better diabetes training to physicians, as well as supporting them with nurses trained in diabetes care and peer-support groups (Anzaldo-Campos et al., 2016). Further, the additional monitoring and support of patients via the use of mobile phone technology was tested in a second intervention group, given the common use of mobile phones in Mexico. First results indicated a significant reduction in HbA1c and better diabetes knowledge in both intervention groups compared to standard care. The use of the mobile phone technology did not lead to statistically significant improvements compared to the other intervention group. Other studies investigating the use of mobile phone technology have, however, shown promising results (Singh et al., 2016). Two randomized controlled trials investigated ways to improve diabetes outcomes in Costa Rica and China, respectively (Goldhaber-Fiebert et al., 2003; Sun et al., 2008). In Costa Rica, the application of a community-based nutrition and exercise program led to reductions in weight, fasting glucose and HbA1c levels. In Shanghai, China, more extensive diabetes education and the provision of meal plans led to improvements in blood glucose, HbA1c levels, blood pressure and waist-to-hip ratios compared to the group receiving standard diabetes education. Unfortunately, so far information about the ultimate value of these interventions in terms of their cost-effectiveness and long term effects is scarce, partly because the investigation is still under way (Anzaldo-Campos et al., 2016) or has not (yet) been evaluated (Singh et al., 2016).

Further, in MICs the provision of universal healthcare has been advocated as

a means to reduce health inequities by providing everyone with the ability to access healthcare (Marmot et al., 2008). Mexico has been one of the countries where the goal of universal healthcare has been almost accomplished through the introduction of "Seguro Popular", which provides those without prior health insurance coverage with social security and access to diabetes treatment options (Knaul et al., 2012; Rivera-Hernandez et al., 2016). However, evidence on the impact of diabetes treatment and outcomes has shown that the availability of this program has only led to very modest improvements, only finding a positive effect on the use of pharmacological therapy. No effects were found on the monitoring of blood glucose or adherence to exercise plans by people with diabetes (Rivera-Hernandez et al., 2016). A likely reason for this, brought up by the authors, was that many clinics were not prepared to provide specialized diabetes care and medications, suggesting that barriers to accessing appropriate diabetes care and education still existed. Hence, while public healthcare provision for those previously uninsured can reduce inequities, such programs need to ensure that their efforts are not sabotaged by the low quality of the offered services.

The overall disease burden and structural constraints

The mentioned strategies may be able to reduce the diabetes burden, however, they mostly focus on diabetes without taking into account the overall disease burden nor existing structural constraints existent in MICs that could significantly limit the applicability and sustainability of interventions. They therefore tend to represent temporary solutions aiming to address specific needs of people at risk of or living with diabetes under the current circumstances, but may not help to substantially reduce the burden of diabetes in the long term.

One constraint to the successful implementation of above mentioned interventions is the wider disease burden, which may inhibit the healthcare system from providing effective treatment for diabetes and other chronic diseases. However, integrating diabetes care with the healthcare for other diseases may also present a viable opportunity for healthcare systems in MICs.

Health systems in developing countries have been slow to adopt technologies to reduce the burden of communicable diseases, maternal and perinatal conditions as well as nutritional deficiencies (Gutiérrez-delgado et al., 2009). The main reasons for this slow adoption are social and political instability limiting long-term planning, a lack of resources to finance the introduction of health technologies, and a dearth of qualified personnel in the public sector due to a lack of training and the greater attractiveness of the private sector and developed countries (Gutiérrez-delgado et al., 2009). Therefore, many MICs face a double disease burden with high rates of communicable and non-communicable diseases at the

same time (Gutiérrez-delgado et al., 2009). The treatment of non-communicable diseases (NCDs) places additional pressure on health systems that did mainly develop to provide acute care of infectious diseases based on single-visit treatments, and are lacking the infrastructure, resources and experience for the treatment of chronic diseases such as diabetes (Nulu, 2016). Policy makers in MICs therefore are forced to make decisions about the prioritization of treatments in an effort to use the available resources in a cost-effective as well as equitable manner (Gutiérrez-delgado et al., 2009), potentially limiting a systems ability to provide effective diabetes care.

To improve treatment for diabetes under these circumstances, a greater integration of health services and control efforts for diabetes with the treatment of communicable diseases and other NCDs could help to exploit synergies and interactions between diseases. One such example presents the relationship of diabetes with tuberculosis, with diabetes patients have a two- to threefold higher risk to develop tuberculosis in many LMICs. Apart from the burden of an additional disease, tuberculosis may also complicate glucose management in people with diabetes (Dooley et al., 2009). Therefore, instead of competing for resources, the detection and treatment of both diseases may be integrated to reduce costs and improve health outcomes (Marais et al., 2013; Remais et al., 2013). Because tuberculosis and other communicable diseases are more common in groups of lower socioeconomic status with less access to high quality care, the double burden with diabetes and the interplay between the diseases has the potential to even further increase the already existing health and social inequities (Marais et al., 2013). Similarly, diabetes is often accompanied by other NCDs that share risk factors with diabetes and are further worsened by high blood glucose levels (Cheung et al., 2012). In particular, hypertension often appears together with diabetes (Barquera et al., 2013; Cheung et al., 2012), is very prevalent in MICs and one of the major causes of mortality (Mills et al., 2016), offering another avenue for treatment integration to improve health outcomes by better using existing resources. Hence, focusing on ways to take advantage of the synergies presenting themselves in the treatment of communicable and non-communicable diseases could provide a way to reduce the overall disease burden, in particular, of more marginalized populations, which could also reduce the existing inequities while limiting the strain on healthcare budgets.

Studies have also consistently shown a relationship of early life health with later life health outcomes, suggesting that bad health and nutritional status early in life could increase the risk to develop diabetes and other diseases later (Currie et al., 2013; Hanson et al., 2012). Therefore, efforts to improve maternal and early life health outcomes of children will not only have short-term effects but likely help to prevent adverse health outcomes later in life (Bygbjerg, 2012; Marais et al.,

2013). As a result, investing in the treatment of infectious diseases, nutritional deficiencies and maternal health could help to reduce the overall disease burden now and in the future. Further, because the poor are likely most exposed to the risk of adverse early life events, such efforts could help to reduce the economic inequities found in this thesis.

However, while a greater integration of diabetes care with the care of other diseases may be a viable way forward, such changes in the formal health-care sectors will not be sufficient. Because of the feedback loops between poverty and bad health, i.e. poor people are more likely to be sick which then further worsens their economic situation, socioeconomic inequities themselves are drivers of the disease burden (Di Cesare et al., 2013). Consequently, structural problems such as an unequal distribution of power, financial resources, the access to education, a healthy living environment, affordable housing as well as to high quality health-care, need to be addressed. Only this will help to achieve lasting reductions in inequalities and consequently also the disease burden due to both communicable and non-communicable diseases (Di Cesare et al., 2013).

Discrimination of people with diabetes

Despite the proposed efforts to reduce inequities in the burden of diabetes, people with diabetes may still face discrimination. The thesis has found considerable adverse effects of diabetes on employment chances which may not only be explained by its health impact, but also by employers discriminating against people with the disease. Once employers are aware of the employee's diabetes, they may decide to replace the employee with a healthy person as they suspect reductions in productivity due to health problems or disease management at the workplace. Little information exists regarding the importance of discrimination of employers against people with diabetes in LMICs. For the USA, studies show that people with diabetes were more likely to experience discharge, constructive discharge or suspensions affecting their ability to retain their job (McMahon et al., 2005). Further, working for smaller employers, being older and the ethnic background affected the risk of experiencing discrimination due to diabetes in the workplace. Similarly, a study for Switzerland found that people with diabetes were less likely to be hired and diabetes related events—such as hypoglycemia—made it more likely to experience job loss (Nebiker-Pedrotti et al., 2009). Even though we have no information about the importance of discrimination for the employment effects found in this thesis, given the evidence from HICs it is likely that it plays a considerable role. The adverse effects for the poor and informally employed suggest that discrimination may play a more important role in manual occupations that value physical health to a greater extent than more brain based jobs

in the formal sector. Additionally, informal jobs are not affected by job security legislation (Loayza et al., 2011; Ulyssea, 2010), reducing the costs of lay-offs and of hiring and training a new employees, making it easier to replace an 'unhealthy' with a 'healthy' employee, further incentivising discrimination against people with diabetes.

Unfortunately, simple remedies for this type of discrimination may not exist in MICs. Because informal labour markets are a substantial part of transition economies, legislative measures to reduce the incentives of discriminating against people with diabetes may fall short—at least partly—as they would not be enforceable in the informal sector. Further, stricter protection legislation may have counterproductive effects in MICs if they lead to reduced hirings of people with diabetes or those at a higher risk to develop diabetes, such as overweight or obese candidates (Muravyev, 2014). Companies may be inclined to demand health check-ups prior to hiring to prevent the employment of personal with a higher risk of adverse health outcomes. Therefore, measures to reduce discriminatory behaviour by employers in MICs should also aim at reducing prejudices about people with diabetes by increasing the knowledge about the disease, its treatment the potential to prevent its adverse health consequences.

Overall it seems that for MICs, national policies to change food consumption behaviours to prevent diabetes could currently be the best option to halt the escalation of the economic impact of diabetes and to reduce inequities. The results of this thesis suggest that it should be a priority to design interventions that address the existent inequities by preventing diabetes in those populations that experience the worst economic consequences, i.e. the poor and more marginalised groups of a country. One way to reduce the existing inequities using the existing healthcare system would be the integration of the treatment of diabetes with already existing strategies to treat related communicable diseases that are common in underserved populations. This would also reduce competition for resources to treat different diseases, a problem facing many decision makers in very resource constrained healthcare systems. The evidence base for the effectiveness of screening programs, preventative pharmacological treatment and lifestyle interventions is less conclusive, potentially due to the social and economic structural constraints existent in many MICs, preventing their successful implementation. Therefore, the structural problems underlying the already existing social, economic as well as health inequities will need to be addressed to achieve long term reductions in the burden of diabetes. This also pertains to issues of discrimination of people with diabetes at the workplace, currently being mostly unprotected from such behaviour due to the large informal labour markets in MICs.

Strengths and limitations

The strengths and limitations of each study and the used methodological approach have been evaluated within each chapter. Additionally, the thesis overall has strengths and limitations.

A strength of this thesis is the provision of a comprehensive overview and assessment of the state of economic research on the impact of diabetes. It provides other researchers guidance by identifying areas for future research and suggestions on which methods to use. Further, the thesis itself fills some of the identified gaps by investigating the impact of diabetes on labour market outcomes in MICs. A strength of these analyses is the use of rigorous econometric approaches taking advantage of available and previously underexplored, high quality, household data, allowing to investigate a variety of topics in the absence of experimental data. One of the challenges was the choice of the most appropriate method to establish a causal relationship. The main concern was that unobserved variables, measurement error as well as reverse causality may introduce bias into the estimates. A variety of methods were used that each had advantages and disadvantages in terms of the underlying assumptions and the ability to account for potential sources of bias. Their choice was mainly guided by the available data and the best way of achieving a causal interpretation under the given circumstances. Nonetheless, regardless of the method used, results consistently showed an adverse relationship of self-reported diabetes with employment probabilities, suggesting a relatively robust and likely causal effect. The methods used also improved upon previous approaches, providing more robust evidence and also incorporated methods predominantly known in epidemiology.

A further strength is the provision of evidence on the potential of diabetes to widen the economic inequities in developing countries, identifying the groups that were disproportionally affected by the disease. Further, it has also advanced the understanding of diabetes as a multifaceted condition by exploring effects over time and for those who are aware and those who are unaware of their diabetes. Finally, it provides evidence from different data sources and contexts and also investigates the value of becoming aware of the disease through a diagnosis and its ability to influence health behaviours.

The thesis has several limitations. Whilst the intention was to provide evidence on the economics of diabetes in MICs, the thesis mostly investigates the economic impact of diabetes. While this provided important information for researchers and policy makers, the thesis did not investigate how to curb this economic diabetes burden. Information about the best and most costs-effective interventions that could be applied in MICs to lower the burden of diabetes is urgently needed as information about who is affected most will not suffice to effectively reduce the

burden. Research on how to implement interventions feasible in non-HIC settings is therefore of paramount importance, but was beyond the scope of this thesis.

This leads to the next limitation. The thesis does not investigate in how far healthcare systems in MICs need to change in order to better provide care. Because they often lack financial resources, do not efficiently use the available resources, are designed to treat acute infectious diseases rather then affecting the outcomes of long-lasting non-acute NCDs, and often provide unequal access to their health services due to financial constraints of those seeking care, research into how to better equip healthcare systems to confront the challenges of treating NCDs is urgently needed (Guzman et al., 2010; Mills, 2014).

A further limitation is the geographical concentration of the thesis, as far as the empirical, analytical chapters are concerned. While Mexico and China are among the ten countries worldwide regarding the absolute size of their population with diabetes, there are other large and small MICs currently facing similar challenges (NCD Risk Factor Collaboration, 2016). It cannot be assumed that the evidence provided in this thesis is perfectly representative of all other MICs. There is hence a need to investigate the economic burden and potential solutions in other countries, given their own specific context in terms of culture, the political system, economic development and existing inequities.

Finally, while the thesis intended to provide a picture of the potential inequities in the economic impact of diabetes for socioeconomic subgroups, it did not investigate in detail why these inequities exist and could only speculate on the reasons. A better understanding of the underlying reasons will be essential for designing adequate strategies to address these inequities. Further, whilst the thesis has touched upon the potential reasons for the differences in employment effects between those self-reporting diabetes and those unaware, it has not provided an in depth analysis of this phenomenon. A better identification of the underlying reasons will be required to design interventions that can prevent the adverse economic effects of diabetes.

Suggestions for future research

This thesis has shown the global economic impact of diabetes and its adverse effect on labour market outcomes in Mexico and China. It identified the poor, those in the informal economy and women as being most adversely affected by the disease. It further found that, at least in China, it is men that appear to make the most from a diabetes diagnosis in terms of positively changing their health behaviours. Finally, it provided some indication that while self-reported diabetes is related to adverse labour market effects, undiagnosed diabetes is not. Without a greater understanding of the underlying reasons for these differences,

it will be difficult to design policies that can help prevent the burden of diabetes in MIC and reduce inequalities.

Several reasons for the observed gender differences in the impact of diabetes have been discussed in this thesis, including biological reasons that increase the risk of complications in women (Arnetz et al., 2014; Catalan et al., 2015; Engelmann et al., 2016; Peters et al., 2015, 2014a; Policardo et al., 2014; Roche et al., 2013; Seghieri et al., 2016) and may also impair the ability of women to lose weight (Penno et al., 2013), as well as differences in the access to appropriate healthcare (Penno et al., 2013). One strategy to further investigate these differences would be the use of biomarker data in combination with information on healthcare utilization as well as socioeconomic outcomes. This could then be used to investigate potential heterogeneities in the relationship between diabetes and overall metabolic health with labour market outcomes. Further, information on healthcare usage could be used to investigate if differences in healthcare access mediate the economic impact of diabetes. A potentially rich source of information is provided by two Chinese household surveys, the China Health and Nutrition Survey (CHNS) and the China Health and Retirement Longitudinal Study (CHARLS). Both contain an extensive list of measured biomarkers and socioeconomic variables that could help to investigate gender differences in metabolic risk. Because biomarker data were only available for one wave in both the CHNS and CHARLS, in the present studies they could not be used longitudinally to predict future effects of diabetes. However, they will be able to be used for this purpose in future waves. This information may also be used to further explore differences in metabolic risk between people aware and unaware of their diabetes. Also, studies measuring potential mediating variables—such as knowledge, motivation, treatment, diabetes control and complications—would help clarify the causal mechanisms through which diabetes affects economic and other outcomes. Structural equation and mediation models could be useful with such data.

Researchers should also try to confirm the results regarding the identified inequities, using different data and countries. Whether these relationships can be confirmed or not, the underlying drivers of these inequities need to be explored to design adequate policies. This could be done by identifying countries where these inequities may not have been found, to isolate the causal determinants. Further, strategies implemented currently or in the future in MICs that aim at reducing these inequities, such as the implementation of universal health insurance schemes, need to be evaluated in how far they are actually achieving this goal in terms of diabetes. The same is true for population level interventions such as taxes on foods or nutrients, as these are probably regressive and theoretically should reduce consumption in particular for those with lower levels of

income (Mytton et al., 2012). This could then lead to a reduction in diabetes incidence in these groups. However, depending on the price elasticities of the taxed products, such taxes may only reduce the disposable income of the poor, leading to reductions in the consumption of other, potentially healthier foods. They therefore may be seen as taxes on the poor, raising political and ethical dilemmas. Further, substitution effects with equally untaxed products may only cause a shift in consumption towards other equally unhealthy, but untaxed products (Mytton et al., 2012).

The population with diabetes in all countries, but especially in LMICs is only partially observed. In other words, many people with diabetes are not aware that they have the disease. This thesis has provided an investigation of the differences between those who are aware and unaware in Chapter 4. It, however, still remains unclear to what extent different factors such as health information and actual health status are causing the observed heterogeneity in the economic impact. Because increasingly household surveys are providing biomarker data in combination with socioeconomic information, they should be used together with quasi-experimental econometric techniques to investigate this topic. A regression-discontinuity design may be used in a similar vein as in Zhao et al. (2013b), who use cut-off values for hypertension to identify those newly diagnosed and the subsequent effect of this diagnosis on health behaviours. A similar approach could be used to explore the effects of a diabetes diagnosis and the entailed health information on labour market outcomes, health behaviours and other economic outcomes. Importantly, research should assess the heterogeneity of effects across income groups, rural versus urban, education levels and between males and females. This would provide important information for designing interventions to reduce the physiological and economic burden of diabetes while preventing a widening of inequities.

Finally, there is a need to explore further economic downstream effects of the economic impact of diabetes. If diabetes causes reductions in employment and potentially also income, it is likely that these will cause not only problems for the individual directly affected, but for the entire household as well. In MICs, where social security is less extensive and comprehensive, adverse health shocks due to diabetes could have consequences for children, spouses or other family members living in affected households (Alam et al., 2014). The loss in labour income due to diabetes needs to be compensated either by increasing the labour supply of other household members or by reducing expenditures for other consumption goods. Both could affect children directly, for example by reducing the time for or the quality of education when tuition fees cannot be paid any more, and also by having to substitute time for education with labour time. Similarly, spouses may be forced to increase their labour supply, reducing the time they can care

for their children. These effects have remained unexplored for diabetes but given the scale of the diabetes epidemic may not be trivial.

Conclusion

Diabetes presents a major challenge for MICs, but evidence on its economic effects has been scarce. This thesis has found that diabetes has an adverse economic impact on individuals and puts a burden on healthcare systems. Because evidence on the impact of diabetes on labour market outcomes was lacking in developing countries, the thesis did focus particularly on this topic. Thereby, it not only provided evidence of the adverse impact of diabetes on employment, but also improved upon previously used econometric methods by using novel strategies to identify a causal relationship. The thesis also identified potential inequities in the impact of diabetes, pointing to larger adverse effects for the poor, those in the informal labour market and women. But the thesis did not only focus on the economic impact of diabetes, but also investigated the effects of a diabetes diagnosis on health behaviours, unravelling evidence for differences in the ability to change health behaviours between men and women.

These findings suggest that there is a need to reduce the economic impact of diabetes in MICs. Considering the increasingly earlier onset of diabetes and the ongoing increase in incidence in many countries, the non-trivial adverse economic effects could otherwise hinder economic development and present a substantial poverty risk. Strategies to combat the adverse diabetes effects need to be tailored to the available resources within countries, target the most affected groups to narrow inequities, also having in mind potential gender differences, structural constraints and the overall disease burden. Finally, there is a large undiagnosed population with diabetes in MICs that is likely to experience severe diabetes complications if identified very late. Hence, ways to diagnose this population earlier in order to prevent further deterioration of health may go a long way in preventing and delaying the most catastrophic economic and health outcomes.

In conclusion, it is hoped that the research presented in this thesis contributes to the knowledge on the economics of diabetes and helps to identify cost-effective strategies to lower the health and economic consequences of diabetes. It has demonstrated the economic burden currently caused by diabetes, in particular in Mexico and China, and has identified groups that are particularly vulnerable to the negative consequences of the disease and should be at the centre of efforts to prevent the burden of diabetes.

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Appendices

I Appendix to Chapter 1

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
DHS	Armenia	Cross-section		2010	women and men 15-49	6700 households	yes	no	yes	diabetes questions, health expenditures	http://www.measuredhs.com/what-we-do/survey/survey-display-354.cfm
DHS	Bangladesh	Cross-section		2011	women 12-49 and men 15-54	17141 households	yes	no	yes		http://www.measuredhs.com/what-we-do/survey/survey-display-349.cfm

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
DHS	Benin	Cross-section		2011-2012	women 12-49 and men 15-64	17422 households	yes	yes	not yet	diabetes questions	http://www.measuredhs.com/what-we-do/survey/survey-display-420.cfm
LSMS	Bosnia and Herzegovina	Cross-section		2004	both sexes	2969 household	yes	no	yes	Diabetes question, healthcare expenditures, employment, earnings	http://go.worldbank.org/OLMHSTUX40

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
LSMS	Bulgaria	Cross-section		2001, 2003, 2007	both sexes	4300 households	yes	no	yes	diabetes questions, since when diagnosed, health expenditures, earnings	http://econ.worldbank.org/

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
Cebu Longitudinal Health and Nutrition Survey	Philippines	Panel	5	1991-2005	Filipino women who gave birth between May 1, 1983, and April 30, 1984	2800 women and 2260 children	no	yes	yes	diabetes, health, nutrition and economic data for mothers available at least since 1991, for children blood samples taken in 2005 and were asked for chronic illnesses	http://www.cpc.unc.edu/projects/cebu/datasets
CHNS	China	Panel	Every 2 years since 1989	1989-2011	both sexes, all ages	Around 16000 people	yes	yes (next wave 2013)	yes	Diabetes question, biomarkers	http://www.cpc.unc.edu/projects/china

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
DHS	Dominican Republic	Cross-section		2007	Women 15-49 and men 15-59	32000 households	yes	no	yes	Diabetes question, (earnings, employment, health expenditures, wealth)	http://www.measuredhs.com/what-we-do/survey/survey-display-291.cfm
DHS	Egypt	Cross-section		2008	Females 15-49 and males 15-59	18968 households	yes	no	yes	Diabetes question, socioeconomic information (earnings, employment, health expenditures, wealth)	http://www.measuredhs.com/what-we-do/survey/survey-display-294.cfm

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
DHS	India	Cross-section		2005	women 15-49 and men 15-54	109041 households	yes	no	yes	diabetes question and history, earnings, employment, wealth	http://www.measuredhs.com/what-we-do/survey/survey-display-264.cfm
Indonesian Family Life Survey	Indonesia	Panel	4	1993, 1997, 2000, 2007	both sexes, all ages	30000 people	almost	no	yes	diabetes question only in last wave	http://www.rand.org/labour/FLS/IFLS.html

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
LSMS	Iraq	Cross-section		2007	both sexes, all ages	18144 households	yes	no	yes	diabetes questions, comorbidities,health expenditures, earnings, employment, wealth	http://go.worldbank.org/HATUQJIMF0
DHS	Lesotho	Cross-section		2009	Women 15-49 and men 15-59	9391 households	yes	no	yes	diabetes questions, earnings, income, wealth	http://www.measuredhs.com/what-we-do/survey/survey-display-317.cfm

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
LSMS	Malawi	From 2013 on partly panel structure		2004, 2010	both sexes	12271 households in 2010	yes	yes	yes	diabetes questions, health expenditures, employment, income	http://go.worldbank.org/RMEFTSE800
MxFLS	Mexico	Panel	2	2002, 2005	both sexes, all ages	35000	yes	no	yes	diabetes question, labour market outcomes, parental diabetes	http://www.ennvih-mxfls.org/es/ennvih.php?seccion=1&subseccion=1&session=76719964140

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
Enquete nationale sur les niveaux de vie des menages	Morocco	Cross-section		2007	?	7200 households	yes	no	no information found	Diabetes question	http://www.hcp.ma/Enquete-nationale-sur a96.html
LSMS	Nepal	Cross-section/Panel	3	1996, 2003, 2010	both sexes	6000 households, Panel 1200	yes	no	yes	diabetes questions, since when diagnosed, health expenditures, earnings, employment	http://go.worldbank.org/LLAVNKC6E0

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
DHS	Peru	Cross-section		2011	only females, 15-49	26182 households	yes	no	yes	diabetes questions, income, health expenditures, employment, wealth	http://www.measuredhs.com/what-we-do/survey/survey-display-433.cfm
DHS	Senegal	Cross-section		2011	Women 15-49 and men 15-59	7902 households	yes	no	yes	diabetes questions, income, health expenditures, employment, wealth	http://www.measuredhs.com/what-we-do/survey/survey-display-365.cfm

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
LSMS	Serbia and Montenegro	Panel	2	2002, 2003	both sexes	19725 persons (2002), 8027 persons (2003)	yes	no	yes	Diabetes question, healthcare expenditures, employment	http://microdata.worldbank.org/index.php/catalog/80
South African National Income Dynamics Study (NIDS)	South Africa	Cross-section	2	2008, 2011	both sexes	7300 households	yes	yes	yes	Diabetes question, taking medication and since when diabetes, income, health expenditures, labour market outcomes	http://www.nids.uct.ac.za/home/

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
LSMS	Tajikistan	Cross-section		2007	both sexes	4860 households	yes	no	yes	diabetes questions, labour market outcomes, health expenditures	http://go.worldbank.org/6TUMCB3K30
LSMS	Tanzania	Panel	2	1994, 2004	both sexes	900 households	no	no	yes	diabetes questions, income, employment, health expenditures	http://go.worldbank.org/9F9RHLXM20
WHO World Health Survey	Worldwide	Cross-section		2002	both sexes		yes	no	not directly	Diabetes question	http://www.who.int/healthinfo/survey/instruments/en/index.html

Table A1: Household surveys from low- and middle-income countries including diabetes information as of 2014

Name	Country	Cross-section / Panel	Waves	Years	Population	Sample size	Nationally Representative	Ongoing	Data available	Interesting content	URL
Russia Longitudinal Monitoring Survey (RLMS)	Russia	Panel	15	1994-2011	both sexes	4000-6000 households	yes	yes	yes	diabetes question, time of diagnosis, health expenditures, labour market outcomes	http://www.cpc.unc.edu/projects/rlms-hse

LSMS Living Standards Measurement Surveys **DHS** Demographic and Health Survey

II Appendix to Chapter 2

What is endogeneity?

Endogeneity is a statistical problem that occurs in regression models if the assumptions about the flow or direction of causality are incorrect. If endogeneity is ignored, it could be that claims about causality between two variables or the magnitude of the effect are false. In general, one can only be certain about a causal relationship of the effect of x on y if the following three conditions are met (Antonakis et al., 2012):

- y follows x temporally
- y changes as x changes (and this relationship is statistically significant)
- no other causes should eliminate the relation between x and y.

There are three major causes of endogeneity that violate the conditions above.

1. **Omitted variables** When a regression is run to determine the causal effect of variable x on variable y, but there are unobserved variables that affect variables x or x and y simultaneously, the estimated effect of x on y will be biased. For the case of type 2 diabetes and employment probabilities, there is the danger that, e.g., personal traits like ambition, which are hard to observe, could influence the probability of developing type 2 diabetes through their effect on a person's lifestyle, but they could also simultaneously affect the chances of employment through their influence on a person's determination to find work or to perform well at work. If we are not able to control for this, then our estimate of the effect of diabetes on employment probabilities might, at least partially, represent the effect of personal traits on employment probabilities. As a result, our estimate of the effect of diabetes is biased and does not represent the true size of the relationship between the two variables.

2. **Simultaneity** Simultaneity is present if our outcome variable y and our variable of interest x influence each other simultaneously, so that y not only is affected by x but x is also affected by y. In the case of type 2 diabetes

and labour market outcomes, not only diabetes could influence employment probabilities or work related income, but also resulting changes in lifestyle due to employment or an increase in income could affect the probabilities of developing diabetes. Due to an increase in income people could change their diet or change towards a less active lifestyle which in turn would make them more likely to develop type 2 diabetes.

3. **Measurement error** Measurement errors occur when the independent variable x is imprecisely measured. Here this would be the case if people in a survey did not remember if they have been diagnosed with type 2 diabetes and gave a wrong answer.

There are several solutions to the problem of endogeneity, but only using IV techniques has the potential to deal with all three causes of endogeneity at once. Endogeneity is a problem, because the variable of interest, here diabetes, is correlated with the error term of the estimated model, which includes all omitted variables as well as the effect of y on x and if measurement error is present, the true values. To do this, one needs to find a suitable instrument that needs to fulfil the following conditions:

- it has to be causally related to the endogenous variable x and
- it should not be correlated to the dependent variable y other than through its correlation with x.

This instrument is then used in a first regression to obtain predicted values of the problematic endogenous regressor. Because the instrument is not correlated with the error term, these predicted values of the endogenous variable will be uncorrelated as well and can then be used in a second regression to predict the dependent variable y. The estimated coefficients of this second stage can then be regarded as consistent estimates.

In the case of type 2 diabetes and labour market outcomes, an instrument has to predict the development of diabetes without being otherwise causally related to any of the labour market outcomes, be it employment probabilities, wages or some other measure of productivity. The instrument of choice so far has been the family history of diabetes. It has been shown that a considerable part of the risk of developing type 2 diabetes is hereditary (Hemminki et al., 2010; Herder et al., 2011; The Interact Consortium, 2013). This fact is exploited when the instrument is used and it is assumed that this is the only pathway through which a family history of diabetes affects a person's diabetes risk, and also that, e.g., parental diabetes does not affect the person's labour market outcomes directly.

The most common estimation techniques for the estimation of IV regressions are the linear IV model and the bivariate probit model. The latter is often

deemed more apt for models where both the outcome as well as the instrumental variable are binary, so either 0 or 1, which is the case for employment as an outcome variable as well as diabetes family history as an instrument. Nonetheless, there is some discussion in the econometrics literature regarding the best method to estimate these cases, as it also has been argued that because the linear IV technique does not depend on the assumption of normality of the error terms, in contrast to the bivariate probit model, its results are more reliable in the case of non-normality, but can sometimes lead to imprecise estimators which can no longer be interpreted meaningfully (Chiburis et al., 2012). Both methods can be found in the reviewed papers.

Country codes

Table A2: Country Codes

Country	Country code	Country	Country code
35 developing countries	LMIC	Jamaica	JAM
Argentina	ARG	Japan	JPN
Australia	AUS	Latin America and Caribbean	LAC
Bahamas	BHS	Mexico	MEX
Barbados	BRB	Netherlands	NLD
Belgium	BEL	Nicaragua	NIC
Bolivia	BOL	Nigeria	NGA
Brazil	BRA	Norway	NOR
Canada	CAN	Pakistan	PAK
Chile	CHL	Panama	PAN
China	CHN	Paraguay	PRY
Colombia	COL	Peru	PER
Costa Rica	CRI	Serbia	SRB
Cuba	CUB	Spain	ESP
Czech Republic	CZE	Sudan	SDN
Denmark	DNK	Sweden	SWE
Dominican Republic	DOM	Switzerland	CHE
Ecuador	ECU	Taiwan	TWN
El Salvador	SLV	Thailand	THA
Europe	EUR	The Bahamas, Barbados, Jamaica, Trinidad and Tobago	CARICOM
France	FRA	Trinidad and Tobago	TTO
Germany	DEU	United Arab Emirates	ARE
Guatemala	GTM	United Kingdom	GBR
Guyana	GUY	United States	USA
Haiti	HTI	Uruguay	URY
Honduras	HND	Venezuela	VEN
Hong Kong	HKG	WHO African Region	AFR
India	IND		

Table A2: Country Codes

Country	Country code	Country	Country code
Iran, Islamic Rep.	IRN		
Ireland	IRL		
Israel	ISR		
Italy	ITA		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Smith-Spangler et al. (2012)	2002–2003	35 LMIC	121051	General pop.	Patient	RB/M	$				3 at 50th percentile to 157 at 95th percentile	3.40 at 50th percentile to 178 at 95th percentile		
Boutayeb et al. (2014)	NA	Various Arab countries	NA	General pop.	Healthc. system	SAM	USD				UDD 529[j]			
Barceló et al. (2003)	2000	ARG	1250300	General pop.	Societal	SAM	ARS	16547	1130	15416[b]	597[a]	904[a]	8145[a]	12330[a]
Davis et al. (2006)	2000–2051	AUS	1294	General pop.	Healthc. system	SDS	AUD		1514 (2000), 2282 (2051)		3496[a] (2000)	3379[a] (2000)		
Barceló et al. (2003)	2000	BHS	12800	General pop.	Societal	SAM	BSD	43	25.2	16	1605	2507	1009	1575
Abdulkadri et al. (2009)	2001	BHS	10435	General pop.	Societal	SDS	BSD	233	17	216[b]	836[a]	1310[a]	10789[a]	16914[a]
Abdulkadri et al. (2009)	2001	BRB	28438	General pop.	Societal	SDS	BBD	75	69.2	5	2455	2433	204	202
Barceló et al. (2003)	2000	BRB	23300	General pop.	Societal	SAM	BBD	307	26	281[b]	1099[a]	1117[a]	11880[a]	12076[a]

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Jönsson (2002)	1999	BEL	735 patients	General pop.	Healthc. system	SAM	EUR		1561		3295	4704		
Jönsson (2002)	1999		7000 (overall)	General pop.	Healthc. system	SAM	EUR				2834	Not possible because no country specific estimate		
Barceló et al. (2003)	2000	BOL	153900	General pop.	Societal	SAM	BOB	901	338	563[b]	3435[a]	2199[a]	5717[a]	3659[a]
Barceló et al. (2003)	2000	BRA	4532600	General pop.	Societal	SAM	BRL	54892	9598	45294[b]	1595[a]	2118[a]	1595[a]	9993[a]
Lau et al. (2011)	2008–2035	CAN	147498 with diabetes	Four Alberta Health and Wellness databases	Healthc. system	SAM	CAD		5934 (2007); 20032 (2035)		4563[a]	4023[a]		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Pohar et al. (2007b)	1993–2001	CAN	57774	Saskatchewan Canadians (excluding Indians)	Healthc. system	SAM	CAD				large urban: 3563 (1993), 3454 (2001), small urban: 3321 (1993), 3427 (2001), rural: 3368 (1993), 3289 (2001)	large urban: 2665 (1993), 3591 (2001), small urban: 3453 (1993), 3563 (2001), rural: 3502 (1993), 3420 (2001)		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Pohar et al. (2007a)	2001	CAN	5284 (Indians) + 41630 (general pop.) with diabetes, 11692 (Indians) + 98680 (general pop.) without diabetes	Registered Indians according to the Indian Act	Healthc. system	RB/M	CAD				Excess costs: Indians 2227, General pop. 2378 (total costs with diabetes: 3622 for Indians/ 3253 in general pop., controls: 1,395 for Indians/ 875 for general pop.)	Excess costs: Indians 2316, General pop. 2473: (total costs with diabetes: 3766 for Indians / 3382 in general pop., controls: 1450 for Indians / 910 for general pop.)		
Barceló et al. (2003)	2000	CHL	496500	General pop.	Societal	SAM	CLP	5890	719	5171[b]	320601[a]	1447[a]	2307131[a]	10416[a]

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Wang et al. (2010)	2007	CHN	1478	T2D patients in these Chinese hospitals	Healthc. system	Survey	RMB				4564 (median), 7926 (mean)	1246 (median), 2164 (mean)		
Wang et al. (2009b)	2007 and 2030 (projection)	CHN	2040	Inpatients and outpatients with DM in 20 hospitals	Societal	Survey	RMB	72916 (2007), 132472 (2030)	67946 (2007), 123187 (2030)	4982 (2007), 9058 (2030)	11555	3401	1586	467
Yang et al. (2012)	2009–2010	CHN	1232 (diabetes), 1201 (no diabetes)	General pop.	Healthc. system	RB/M	RMB				4135 (3.38 times greater than controls)	1136 (3.38 times greater than controls)		
Wang et al. (2009a)	2007	CHN	2054	T2D patients in these Chinese hospitals	Healthc. system	Survey	RMB				4800 (median), 10164 (mean)	1412 (median), 2991 (mean)		
extcite-Gonzalez2009b	32 years	COL	NA	Average Columbian type 2 DM patient	Societal	SAM	COP	5.3	1.8	3.5	611750	570	1187000	1106

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Barceló et al. (2003)	2000	COL	937700	General pop.	Societal	SAM	COP	7737	1241	6496[b]	923826[a]	1323[a]	4836001[a]	6928[a]
Barceló et al. (2003)	2000	CRI	154900	General pop.	Societal	SAM	CRC	1026	210	817[b]	192194[a]	1353[a]	749278[a]	5274[a]
Barceló et al. (2003)	2000	CUB	592400	General pop.	Societal	SAM	CUP	1721	923	798[b]	1219[a]	1558[a]	1054[a]	1347[a]
Horak (2009)	2007	CZE		Insured in health-care system (63.1% of pop.)	Healthc. system	SAM	CHK		190					
Gyld-mark et al. (2001)	1993	DNK	948	General pop.	Societal	WTP	DKK						1128 (mean), 300 (median)	191 (mean), 51 (median)
Barceló et al. (2003)	2000	DOM	254100	General pop.	Societal	SAM	DOP	1410	509	901[b]	14580[a]	2003[a]	25801[a]	3545[a]
Barceló et al. (2003)	2000	ECU	267300	General pop.	Societal	SAM	USD	2830	1104	1727[b]	873[a]	4129[a]	1366[a]	6460[a]
Barceló et al. (2003)	2000	SLV	219400	General pop.	Societal	SAM	SVC	1385	381	1004[b]	626[a]	1737[a]	1650[a]	4577[a]

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Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Honkasalo et al. (2014)	2005–2010	FIN	1890 with T2D	People with T2D in two cities in Finland	Healthc. system	SDS	EUR				1038	1087		
Ricordeau et al. (2003)	1998, 2000	FRA	704423 (1998), 1145603 (2000) with diabetes	Metropolitan France	Healthc. system	RB/M	EUR		2784 (1998), 3268 (2000)		1529 (1998), 1655 (2000)	2107 (1998), 2241 (2000)		
Jönsson (2002)	1999	FRA	751 patients	General pop.	Healthc. system	SAM	EUR		5478		3064	4214		
Jönsson (2002)	1999	DEU	809 patients	General pop.	Healthc. system	SAM	EUR		1653		3576	4752		
Köster et al. (2006)	2001	DEU	306736 (26971 with diabetes)	General pop.	Societal	RB/M	EUR		Excess: 19364 (total: 40650)		Excess 2507 (total 5262)	Excess: 3329 (total: 6987)	Excess 1328 (total: 5019)	Excess: 1763 (total: 6664)
Köster et al. (2011)	2000–2007	DEU	320000 (2000) to 275000 (2007)	AOK Hessen	Healthc. system	RB/M	EUR		17299 (2000), 25614 (2007)		2400 (2000), 2605 (2007)	3493 (2007), 3218 (2000)		
Martin et al. (2007)	1995–2003	DEU	3268	Newly diagnosed T2D patients	Healthc. system	SAM	EUR				3210	4075		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Köster et al. (2012)	2000–2009	DEU	not given, only DM patients stated (30472)	AOK Hessen	Healthc. system	RB/M	EUR		21230 (2000), 26226 (2009)		2779 (2000), 2611 (2009)	3471 (2000), 3261 (2009)		
Barceló et al. (2003)	2000	GTM	368700	General pop.	Societal	SAM	GTQ	2535	878	1657[b]	6131[a]	2382[a]	11572[a]	4495[a]
Barceló et al. (2003)	2000	GUY	28400	General pop.	Societal	SAM	GYD	141	80	62[b]	131041[a]	2800[a]	102135[a]	2182[a]
Barceló et al. (2003)	2000	HTI	79500	General pop.	Societal	SAM	HTG	249	152	97[b]	12782[a]	1912[a]	8175[a]	1223[a]
Barceló et al. (2003)	2000	HND	193000	General pop.	Societal	SAM	HNL	772	366	405[b]	8750[a]	1898[a]	9680[a]	2100[a]
Chan et al. (2007)	2004	HKG	147	T2D patients attending the DM outpatient clinic at a public hospital	Societal	Survey	USD				11638	2288	1817[e]	357[e]

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Ramachandran et al. (2007)	1998, 2005	IND	556 with T2D (urban = 309, rural = 247)	T2D patients in India	Patient	Survey	INR				Median values: 10000 (urban), 6260 (rural)	Median values: 773 (urban), 484 (rural)		
Tharkar et al. (2010)	2009	IND	718	Diabetes patients in Chennai city	Societal	Survey	INR		268		25391 (median)	1557 (median)	4970 (median)	305 (median)
Javanbakht et al. (2011)	2009	IRN	4500	Diabetes patients from Tehran and Fars province	Societal	Survey	IRR	9611[h]	5187[h]	4420[h]	8358592	2142	8578816	2199
Esteghamati et al. (2009)	2004, 2005	IRN	710 (T2D), 904 (controls)	Pop. in Teheran	Societal	RB/M	IRR	401 (Teheran); 2117[h] (Iran)	327 (Teheran); 1727[h] (Iran)	74 (Teheran), 390[h] (Iran)	876622 (Teheran)	443 (Teheran)	200146 (Teheran)	101 (Teheran)
Nolan et al. (2006)	1999	IRL	701	T2D patients of four Irish hospitals	Healthc. system	SAM	EUR				2469	2867		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Chodick et al. (2005)	2001	ISR	24632	Insured patients in HMO	Healthc. system	RB/M	ILS		433		6002 (2001), 3926 (1999)	1950 (2001), 1275 (1999)		
Lucioni et al. (2003)	1998	ITA	1263	T2D patients from randomly drawn practices across Italy	Societal	SAM	EUR	8289[d]	7930	359	2991	4588	135[ac]	208[ac]
Bruno et al. (2012)	2003–2004	ITA	33792 (diabetes) and 863123 (no diabetes)	Turin pop.	Healthc. system	RB/M	EUR				2465 (3361 (diabetes), 896 (no diabetes)	3328 (4537 (diabetes), 1210 (no diabetes)		
Morsanutto et al. (2006)	2001–2002	ITA	299	T2D patients who visited a diabetologic center in Italy (DC)	Healthc. system	SAM	EUR				1910	2823		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Marchesini et al. (2011)	2006	ITA	311979	People with DM at 22 local health districts	Healthc. system	RB/M	EUR				2589	3296		
Abdulkadri et al. (2009)	2001	JAM	186036	General pop.	Societal	SDS	JMD	556	454	102	44647	2439	10046	549
Barceló et al. (2003)	2000	JAM	181400	General pop.	Societal	SAM	JMD	1037	345	693[a]	32251[a]	1901[a]	64787[a]	3818[a]
Nakamura et al. (2008)	1990–2001	JPN	4535	Community-dwelling in Shiga	Healthc. system	SAM	JPY				189060 (diabetes), 99900 (non-diabetes)	1674 (diabetes), 884 for (non-diabetes)		
Barceló et al. (2003)	2000	LAC	Diabetes prevalence of 15.2 million	Pop. from all countries in Latin America and Caribbean	Societal	SAM	USD	82304	13529	68774[b]	703[a]	887[a]	3576[a]	4512[a]
Barceló et al. (2003)	2000	MEX	3738000	General pop.	Societal	SAM	MXN	30677	4006	26671[b]	4994[a]	1072[a]	33249[a]	7135[a]

Table A3: COI study characteristics and cost estimates

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								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Arredondo et al. (2005)	2004, 2006	MEX	951417 estimated cases	All users of healthcare in public institutions	Societal	SAM	MXN	290[d]	229	61k	1472[a]	242[a]	386[a]	64[a]
Arredondo et al. (2011b)	2010	MEX	Whole pop.	Population demanding services at Mexican healthcare institutions for T2D	Societal	SAM	MXN	1066	470	596	4016[a]	485[a]	5090[a]	610[a]
Arredondo et al. (2007)	2005	MEX	Whole pop.	General pop.	Patient	SAM	MXN		284 OOP expenditures (52% of overall expenditures)					

Table A3: COI study characteristics and cost estimates

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								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Arredondo et al. (2004)	2003, 2005	MEX	Whole pop.	General pop. using public health-care institutions	Societal	SAM	MXN	532 (2005)	235 (2005)	297 (2005)	1467[a] (2005)	263[a] (2005)	1852[a] (2005)	331[a] (2005)
Rodríguez Bolaños et al. (2010)	2002, 2004	MEX	497	IMSS insured	Healthc. system	SDS	MXN		661 (2004)		35622[a] (2004)	4672[a] (2004)		
Redekop et al. (2002)	1998	NLD	1371 with T2D	T2D patients in the Netherlands	Societal	SAM	NLG	1014[d]	953	61	4023	2780	282[a]	195[a]
Linden et al. (2009)	2000–2004	NLD	2.5 million (641200 with diabetes)	Dutch people with diabetes	Healthc. system	SDS	EUR		571 (2000), 1063 (2004)		974 (2000), 1283 (2004)	1259 (2000), 1658 (2004)		
Jönsson (2002)	1999	NLD	909 patients	General pop.	Healthc. system	SAM	EUR		671		1827	2761		
Barceló et al. (2003)	2000	NIC	136100	General pop.	Societal	SAM	NIO	442	292	150[b]	7922[a]	2145[a]	4082[a]	1105[a]

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Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Suleiman et al. (2006)	July 2003–June 2004	NGA	35	Diabetes patients in out-patient clinic in Nigeria	Patient	SDS	NGN				29366	662		
Solli et al. (2010)	2005	NOR	4.6 million from register data of entire pop.	General pop.	Societal	SDS	NRK	319	242	76	20492[a]	2061[a]	5067[a]	650[a]
Khowaja et al. (2007)	2006	PAK	345	Diabetes patients in Karachi	Societal	Survey	PKR				11580[f]	620[f]	840[e]	45[e]
Barceló et al. (2003)	2000	PAN	120500	General pop.	Societal	SAM	PAB	926	222	704[b]	866[a]	1846[a]	2741[a]	5840[a]
Barceló et al. (2003)	2000	PRY	94300	General pop.	Societal	SAM	PYG	738	244	495[b]	2661903[a]	2587[a]	5397747[a]	5245[a]
Barceló et al. (2003)	2000	PER	606800	General pop.	Societal	SAM	PEN	5627	1533	4094[b]	2890[a]	2526[a]	7717[a]	6746[a]

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Leśniowska et al. (2014)	2009	POL	Whole pop.	All Polish diabetes patients	Healthc. system	SAM	RSD	3396	1910	1486				
Biorac et al. (2009)	2007	SRB	99	T2D patients in health centre in Svilajnac	Societal	Survey	RSD	7579[h]			47865	1610	5548	187
Bjegovic et al. (2007)	2002	SRB	360433 people with T2D in Serbia	Serbian T2D patients	Healthc. system	SAM	RSD		280		12457[a]	761[a]		
Mata et al. (2002)	1998	ESP	1004	Diabetes patients from 29 primary health-care centres	Healthc. system	SDS	EUR				771	1488		
Ballesta et al. (2006)	1999	ESP	517	People with DM in region of Cadiz	Societal	SDS	EUR				2560	4690	1844	3379

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Oliva et al. (2004)	2002	ESP	1675304 to 2010365 depending on assumed prevalence	Diabetes patients in National Health System	Healthc. system	SAM	EUR		4010 (6% prev.)– 4461 (5% prev.)		1290 (6% prev.)– 1476 (5% prev.)	2155 (6% prev.)– 2466 (5% prev.)		
Jönsson (2002)	1999	ESP	1004 patients	General pop.	Healthc. system	SAM	EUR		3679		1305	2453		
Bastida et al. (2002b)	1998	ESP	Whole pop. (exact number not given)	Canary Island pop. with diabetes	Societal	SDS	Pts (pre Euro)	75	47	28	78240	907	47928[b]	556[b]
Elrayah-Eliadarous et al. (2010)	2005	SDN	822	Patients with T2D in Khartoum state in Sudan	Patient	Survey	USD				438	456		
Bolin et al. (2009)	1987 and 2005	SWE	Whole pop.	General pop.	Societal	SDS	SEK	499 (1987), 1045 (2005)	223 (1987), 383 (2005)	276 (1987), 662 (2005)	12102 (1987), 12287 (2005)	1484 (1987), 1507 (2005)	15000[a] (1987), 21253[a] (2005)	1840[a] (1987), 2606[a] (2005)

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Norlund et al. (2001)	1993	SWE	70786 (1677 with diabetes)	Southern Sweden	Societal	RB/M	SEK				19411	2855	14777	2174
Wirhn et al. (2008)	2005	SWE	415990 (19226 with diabetes)	Whole Östergötland population	Healthc. system	RB/M	EUR				18293	2243		
Jönsson (2002)	1999	SWE	773 patients	General pop.	Healthc. system	SAM	SEK		929		24927	3319		
Ringborg et al. (2008)	2004	SWE	8230	Diabetes patients in Uppsala county	Healthc. system	SAM	SEK				33210	3888		
Schmitt-Koopmann et al. (2004)	1998	CHE	1479	T2D patients from randomly drawn practices across Switzerland	Healthc. system	SDS	CHF		561		3004	2030		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Lin et al. (2004)	1998–1999	TWN	20757185 (in 1998), 21089859 (in 1999)	People with DM in National Health Insurance	Healthc. system	SDS	TWD				62617 (1998), 60775 (1999)	3499 (1998), 3396 (1999)		
Chang (2010)	2006–2007	TWN	498	Diabetes patients in out-patient clinics in northern Taiwan	Societal	WTP	TWD			4003			68118	4004
Chi et al. (2011)		TWN	16094	Elderly with DM in Taiwan	Healthc. system	SAM			51		111982	6338		
Chatter-jee et al. (2011)	2008	THA	475	Diabetes patients treated in district hospital	Societal	Survey	TWD				17638	1082	10569	649

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Barceló et al. (2003)	2000	TTO	71300	Pop. from all countries in Latin America and Caribbean	Societal	SAM	TTD	540	72	468[b]	3358[a]	1011[a]	21780[a]	6560[a]
Abdulkadri et al. (2009)	2001	TTO	135093	General pop.	Societal	SDS	TTD	852	227	625	5722	1677	15797	4628
Al-Maskari et al. (2010)	2004	ARE	150	Diabetes patients in Al-Ain District	Healthc. system	Survey	AED				no complication: 5906, with complications: 20774, overall: 16115	no complications: 2047, with complications: 7199, overall: 5585		
Jönsson (2002)	1999	GBR	756 patients	General pop.	Healthc. system	SAM	GBP		244		1558	3065		
Dall et al. (2010)	2007	USA	Diabetes prevalence of 16.5 million	General pop.	Societal	SDS	USD	167862	111257	56604	6414	6751	3263	3434

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Buescher et al. (2010)	1998	USA	127991	Medicaid pop.	Healthc. system	SDS	USD		540		4098	4221		
Dall et al. (2003)	2002	USA	Diagnosed DM prevalence of 12.1 million	General pop.	Societal	SDS	USD	161896	112947	48948	7601[a]	9346[a]	3294[a]	4050[a]
Druss et al. (2001)	1996	USA	23200	General pop.	Societal	Survey	USD	78518	13768	4771	1097	1495	380[ac]	518[ac]
Durden et al. (2009)	2000, 2005	USA	21592 (2000), 127254 (2005)	Employees of large, privately-insured companies	Healthc. system	RB/M	USD				7365 (2000), 7327 (2005)	8349 (2000), 8306 (2005)		
Trogdon et al. (2008)	2000–2004	USA	3790 (diabetes), 42413 (no diabetes)	General pop.	Healthc. system	RB/M	USD				5035[i]	5708[i]		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Brandle et al. (2003)	2000	USA	1364	People with T2D enrolled in managed care programs	Healthc. system	SAM	USD				3715 (median)	4747 (median)		
O'Connell et al. (2012)	2005	USA	32052	American Indians in and around Phoenix, Arizona	Healthc. system	RB/M	USD				5542	6282		
Peele et al. (2002)	1996	USA	20937 with diabetes	Employed DM patients	Healthc. system	SAM	USD		126		4430 (17.9% OOP)	6039 (17.9% OOP)		
Rodbard et al. (2010)	2006	USA	3551 (diabetes), 8686 (no diabetes)	General pop.	Patient	RB/M	USD				233	264		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Honeycutt et al. (2009)	1998–2003	USA	96873 (5289 had diabetes)	General pop.	Healthc. system	SDS and RB/M	USD		61958 (regression), 43452 (attributable fraction)		4240 (regression), 2980 (attributable fraction)	4966(regression), 3490 (attributable fraction)		
Maciejewski et al. (2004)	1998	USA	429918	USA veterans	Healthc. system	SAM	USD		2214		3888[a]	5150[a]		
Birnbaum et al. (2003)	1997–1998	USA	3759 (diabetes), 3759 (without diabetes)	Employed and retired women	Healthc. system	RB/M	USD				5.500 for women <age 65 per year, 25000 for women >= age 65 per year, 233000 lifetime costs	6680[f]or women <age 65 per year, 30362 for women >= age 65 per year, 282973 lifetime costs		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Zhou et al. (2005)	10 year follow up	USA	1223 with T2D	People with DM in Michigan	Healthc. system	SAM	USD				7100 (undiscounted per year over 10 year period)	9072 (undiscounted per year over 10 year period)		
Dall et al. (2008)	2007	USA	Diagnosed DM prevalence of 17.5 million	General pop.	Societal	SDS	USD	185682	123788	62108	6649	7095	3328	3552
Tunceli et al. (2010)	2007	USA	256245 (T2D), 256223 (controls)	Non-institutionalised adults	Healthc. system	SDS and RB/M	USD				Matching: 4217, Disease attributable: 3002	Matching: 4500, Disease attributable: 3204		

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Condliffe et al. (2014)	2007	USA	7514 with diabetes	USA pop. with positive healthcare expenditures in survey	Healthc. system	SAM	USD				11167[g]	11917[g]		
Ramsey et al. (2002)	1998	USA	8748 diabetes patients, 8748 matched controls	Employees of large, privately-insured companies	Employer	RB/M	USD				3842	5021	568	743
Lee et al. (2006)	2000	USA	984 with DM (540 white, 210 African American, 234 Hispanic)	White, African Americans and Hispanics in the USA	Healthc. system	SAM	USD				6616 (6887 if white, 6162 if African American, 5647 if Hispanic)	8453 (8799 if white, 7873 if African American, 7215 if Hispanic)		
Barceló et al. (2003)	2000	URY	119000	General pop.	Societal	SAM	UYU	1202	147	1055[b]	9619[a]	1233[a]	69171[a]	8867[a]

Table A3: COI study characteristics and cost estimates

Ref.	Horizon	Country	Sample size	Population	Perspective	Approach	LCU	Aggregate costs (mill. $)			Per capita costs			
								Total	Direct	Indirect	Direct (LCU)	Direct ($)	Indirect (LCU)	Indirect ($)
Barceló et al. (2003)	2000	VEN	610800	General pop.	Societal	SAM	VEF	4820	317	4503[b]	342[a]	518[a]	2100[a]	7373[a]
Kirigia et al. (2009)	2005	WHO African region	7020000	General pop.	societal	SAM	USD	28610	9090	19520	876	983	10556	11845

T2D type 2 diabetes **DM** Diabetes Mellitus **Healthc. System** Healthcare system **LCU** Local currency unit **Pop.** Population **Prev.** Prevalence **Ref.** Reference **RB/M** regression based/matching **SAM** Sum-all medical **SDS** Sum-diagnosis specific.

[a] Own calculation dividing presented aggregate cost estimate by number of people with diabetes in study.

[b] Total and direct cost estimates were presented in paper and indirect costs calculated, but not explicitly stated. We calculated indirect costs by deducting the presented direct costs estimate from the presented total costs estimate to arrive at an indirect costs estimate.

[c] Calculated the number of people with diabetes by dividing the aggregated direct costs and the per capita direct costs estimate as presented in the study.

[d] Calculated total costs of diabetes for papers summing up direct and indirect costs.

[e] Calculated per capita indirect costs deducting direct from total cost estimate presented in study.

[f] Costs originally presented per visit, to arrive at yearly costs had to multiply costs per visit by number of visits per year.

[g] Per capita direct costs were presented for different groups of diabetics, calculated average costs for person with diabetes by summing up and weighting costs people with diabetes + hypertension, people with diabetes + obesity, people with diabetes + obesity + hypertension.

[h] The study assumes sample would be nationally representative.

[i] Study only reported the adjusted incremental cost ratio of 2.39 compared to the average healthcare expenditures of people without diabetes of USA$3630. To calculate the incremental costs of a person with diabetes we multiplied the average healthcare expenditures of people without diabetes by the given cost ratio .

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Smith-Spangler et al. (2012)	LMIC (2002-2003)	No breakdown of costs provided								
Kirigia et al. (2009)	AFR (2000-2005)	x	x	x	x	x	x	x	x	No exact information on share in expenditures is available
Davis et al. (2006)	AUS (1993-1996)	x	x	x	x	x	x			No exact information on share in expenditures is available
Lau et al. (2011)	CAN (1995-2007)	x	x	x						Hospital, physician
Pohar et al. (2007b)	CAN (1993-2001)	x	x	x	x	x	x			Hospital, medication
Ohinmaa et al. (2004)	CAN (1996)	x	x	x	x	x	x			Hospital, medication
Dawson et al. (2002)	CAN (1998)	x	x	x	x	x				No exact information on share in expenditures is available
Johnson et al. (2006)	CAN (1992-2001)	x	x	x	x					Hospital
Simpson et al. (2003)	CAN (1991-1996)	x	x	x	x					Hospital, prescription drugs
Pohar et al. (2007a)	CAN (1991-2001)	x	x	x						Hospital
Wang et al. (2010)	CHN (2007)	x	x	x				x		Complications, insulin therapy
Wang et al. (2009b)	CHN (2007)	x	x					x		Hospital, outpatient visits
Yang et al. (2012)	CHN (2009-2010)	x	x	x	x	x	x			Hospital, medication

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Wang et al. (2009a)	CHN (2007)	x	x	x	x	x	x	x		No exact information on share in expenditures available
Camilo González et al. (2009)	COL (2007)	No breakdown of costs provided								
Horak (2009)	CZE (2007)	x	x	x	x	x	x			Hospital, medication
Honkasalo et al. (2014)	FIN (2005-2010)	x	x	x	x	x	x			
Ricordeau et al. (2003)	FRA (1998,2000)	x	x	x				x		Hospital, medication
Köster et al. (2006)	DEU (2001)	x	x	x	x	x	x	x		Hospital, medication
Köster et al. (2011)	DEU (2000-2007)	x	x	x	x	x	x	x	x	Hospital, other services (medical devices, remedies, professional home nursing, transportation)
Martin et al. (2007)	DEU (1995-2003)	x	x	x	x	x	x			No exact information on share in expenditures available
Köster et al. (2012)	DEU (2000-2009)	x	x	x	x	x	x	x	x	Hospital, medication
Jönsson (2002)	EUR (1999)	x	x	x	x	x	x	x		Hospital, medication
Chan et al. (2007)	HKG (2004)	x	x	x	x	x	x	x	x	Hospital, outpatient clinic visits
Ramachandran et al. (2007)	IND (2005)	x	x	x	x	x	x			Hospital/surgery, medication
Tharkar et al. (2010)	IND (2009)	x	x	x				x		Hospital, medication
Javanbakht et al. (2011)	IRN (2009)	x	x	x	x	x	x	x	x	Complications, medication

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Esteghamati et al. (2009)	IRN (2004;2005)	x	x	x	x	x	x	x		Hospital, medication and devices
Nolan et al. (2006)	IRL (1999-2000)	x	x	x	x	x				Hospital, ambulatory/drug costs
Chodick et al. (2005)	ISR (1999-2001)	x	x	x	x					Medication and lab/diagnostics
Lucioni et al. (2003)	ITA (1999)	x	x	x	x	x				Hospital, drugs
Bruno et al. (2012)	ITA (August 2003-July 2004)	x	x		x	x				Hospital, drugs
Morsanutto et al. (2006)	ITA (Jan 2001-Aug 2002)	x		x	x	x				Hospital, drugs
Marchesini et al. (2011)	ITA (1997-2006)	x		x	x	x	x			Hospital, drugs
Nakamura et al. (2008)	JPN (1990-2001)	No breakdown of costs provided								
Barceló et al. (2003)	LAC (2000)	x	x	x	x					Medication, complications
Arredondo et al. (2005)	MEX (1989-2003)	x	x	x	x	x				No exact information on share in expenditures available
Arredondo et al. (2011b)	MEX (1990-2008)	x	x	x	x	x				Medication, complications
Arredondo et al. (2004)	MEX (1989-2002)	x	x	x	x	x				Drugs, complications
Arredondo et al. (2007)	MEX (2002-2004)	x	x	x	x	x				Drugs, complications

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Rodríguez Bolaños et al. (2010)	MEX (2002-2004)	x	x	x	x	x	x		x	Hospital, administrative costs
Redekop et al. (2002)	NLD (1998)	x	x	x	x	x	x	x		Hospital, medication
Linden et al. (2009)	NLD (2000-2004)	x			x					Hospital, medication
Suleiman et al. (2006)	NGA (2003-2004)		x		x	x	x	x	x	Drugs, diagnostic tests
Solli et al. (2010)	NOR (2005)	x	x	x	x		x		x	Drugs, medical devices
Khowaja et al. (2007)	PAK (2006)		x		x	x		x		Medicine cost, laboratory costs
Leśniowska et al. (2014)	POL (2005-2009)	x	x	x	x	x	x			Medication, primary care
Biorac et al. (2009)	SRB (2007)	x	x	x	x	x	x			Medication, medical services (incl. ambulatory and hospital costs)
Bjegovic et al. (2007)	SRB (2002)		x	x	x	x	x			No exact information on share in expenditures available
Mata et al. (2002)	ESP (1998-1999)	x	x	x	x	x	x			Drugs, hospital
Ballesta et al. (2006)	ESP (1999)	x	x	x	x		x		x	Medication, hospital
Oliva et al. (2004)	ESP (2002)	x	x	x						Hospital, medication
Bastida et al. (2002b)	ESP (1998)	x	x	x	x	x				Hospital, medication
Elrayah-Eliadarous et al. (2010)	SDN (2005)		x		x	x				Outpatient clinic, drugs
Bolin et al. (2009)	SWE (1987 and 2005)	x	x		x					Hospital, drugs

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Norlund et al. (2001)	SWE (1992-1993)	x	x	x				x		Hospital, home help hours
Wirhn et al. (2008)	SWE (2005)	x	x	x						Hospital, medication
Ringborg et al. (2008)	SWE (2000-2004)	x	x		x	x	x			Hospital, outpatient visits
Schmitt-Koopmann et al. (2004)	CHE (1998-1999)	x	x	x						Hospital, medication
Lin et al. (2004)	TWN (1998-1999)	x	x	x	x	x				No exact information on share in expenditures available
Chi et al. (2011)	TWN (2000)	x	x							Outpatient visits
Chatterjee et al. (2011)	THA (2007-2008)	x	x		x	x		x	x	Informal care, hospitalizations
Abdulkadri et al. (2009)	CARICOM (2001)	x	x	x	x	x				Medication and lab/diagnostics
Al-Maskari et al. (2010)	ARE (2004-2005)	x	x	x	x	x				Hospital (information on other cost components not presented)
Dall et al. (2010)	USA (2007)	x	x	x	x	x	x	x	x	No exact information on share in expenditures available
Ramsey et al. (2002)	USA (1998)	x	x	x	x	x	x		x	Inpatient, outpatient
Buescher et al. (2010)	USA (1998)	x	x	x	x	x	x	x	x	Physician visits, hospital

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Dall et al. (2003)	USA (1998-2000)	x	x	x	x	x	x			Institutional care (nursing home stays, hospital), outpatient care
Druss et al. (2001)	USA (1996)	No breakdown of costs provided. Only self-reported healthcare cost estimate.								
Durden et al. (2009)	USA (2000, 2005)	x	x	x	x	x	x			Hospital, outpatient services
Trogdon et al. (2008)	USA (2000-2004)	No breakdown of costs provided. Only self-reported healthcare cost estimate.								
Brandle et al. (2003)	USA (2000-2001)	x	x		x	x				No exact information on share in expenditures is available
O'Connell et al. (2012)	USA (2004-2005)	x	x	x						Hospital, medication
Peele et al. (2002)	USA (1996)	x	x	x		x				No exact information on share in expenditures available
Rodbard et al. (2010)	USA (2006)	No breakdown of costs provided.								
Honeycutt et al. (2009)	USA (1998-2003)	x	x	x	x	x	x			No exact information on share in expenditures available
Maciejewski et al. (2004)	USA (1998)	x	x							Hospital
Birnbaum et al. (2003)	USA (1997-1998)	No breakdown of costs provided. Only self-reported healthcare cost estimate.								
Zhou et al. (2005)	USA (2000)	x	x	x	x	x	x			No exact information on share in expenditures available
Dall et al. (2008)	USA (2006)	x	x	x						Hospital, medication

Table A4: COI study costing components

Ref.	Country (year of cost data)	Hospital Visits	Outpatient Visits	Physician Visits	Drugs	laboratory	Equipment	Non-medical	Other Costs	Two main cost contributors
Tunceli et al. (2010)	USA (2006-2007)	x	x	x						Hospital, medication
Condliffe et al. (2014)	USA (2004-2007)	No breakdown of costs provided.								
Lee et al. (2006)	USA (2000)		x	x				x	x	Medication, ambulatory

III Appendix to Chapter 3

Linear IV estimates (1st and 2nd stage)

Table A5: Impact of diabetes on employment probabilities (linear IV, 1st and 2nd stage)

	linear IV male				linear IV female			
	(1) Diabetes		(2) Employed		(3) Diabetes		(4) Employed	
Age 25–34	−.001	(.005)	0.151***	(.015)	0.003	(.005)	0.111***	(.015)
Age 35–44	0.016*	(.009)	0.154***	(.019)	0.032***	(.008)	0.198***	(.017)
Age 45–54	0.081***	(.014)	0.098***	(.028)	0.108***	(.014)	0.122***	(.028)
Age 55–64	0.101***	(.016)	−.052	(.039)	0.198***	(.021)	0.001	(.040)
Small city	0.001	(.010)	−.010	(.019)	−.005	(.011)	0.034**	(.017)
City	0.014	(.014)	−.041**	(.020)	−.009	(.013)	0.032*	(.019)
Big city	0.008	(.008)	0.027*	(.014)	−.004	(.009)	0.093***	(.013)
Central	0.011	(.011)	0.024	(.017)	0.015	(.011)	−.035**	(.017)
Westcentral	−.002	(.010)	0.021	(.017)	−.002	(.010)	−.006	(.018)
Northeastcentral	0.007	(.012)	0.005	(.017)	0.009	(.012)	−.051***	(.017)
Northwestcentral	−.006	(.009)	−.033**	(.017)	0.007	(.011)	−.095***	(.017)
Primary	−.009	(.020)	0.060**	(.027)	0.017	(.018)	−.011	(.019)
Secondary	−.003	(.020)	0.056*	(.030)	−.005	(.018)	0.052**	(.021)
Highschool	−.027	(.020)	0.045	(.031)	−.008	(.020)	0.117***	(.026)
College or university	−.018	(.023)	0.057*	(.032)	−.028	(.020)	0.291***	(.025)
Indigenous	0.009	(.010)	0.005	(.017)	0.012	(.013)	−.006	(.018)
Married	0.015**	(.007)	0.086***	(.012)	−.002	(.007)	−.216***	(.011)
Children (under 15)	−.005**	(.002)	0.010**	(.004)	0.003	(.002)	−.016***	(.004)
Wealth	0.003	(.004)	−.001	(.007)	0.003	(.004)	0.030***	(.006)
Parental education	0.019**	(.009)	−.010	(.013)	0.014	(.009)	−.001	(.011)
Diabetes father	0.068***	(.020)			0.035**	(.014)		
Diabetes mother	0.043***	(.016)			0.055***	(.013)		
Diabetes			0.098	(.215)			0.239	(.214)
Constant	−.015	(.022)	0.607***	(.036)	−.020	(.021)	0.289***	(.027)
R2	0.075		0.067		0.090		0.120	
F stat (H0: weak instruements)			20.483				27.706	
Sargan test (H0: valid instruments)			0.862				0.295	
p value			0.353				0.587	
Endogeneity (H0: Diabetes exogenous)			0.864				1.796	
p value			0.353				0.180	
N	6228		6286		8186		8243	

Notes Robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father. Other control variables: age, region, urban, education, indigenous marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results for older age groups

Table A6: Impact of diabetes on employment probabilities by age groups older than 44 (probit)

	45-54		55-64	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	−.083*	−.076**	−.128**	−.033
	(.048)	(.034)	(.056)	(.039)
Log likelihood	−451.544	−764.722	−458.632	−392.174
N	1101	1399	770	847

Notes Average marginal effects; robust standard errors in parentheses. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Instrumental variable analysis for age groups

The results of the bivariate probit models do not indicate endogeneity for the older age group and for males in the younger age group (see Tables A7 and A8), suggesting that particularly for males the results of the more efficient probit model (Table 11) show the true effect of diabetes on employment probabilities. Only for females in the younger age group the test for endogeneity rejects the assumption of exogeneity and the diabetes coefficient—surprisingly—shows a strong positive effect of diabetes on female employment probabilities. Instrument strength, however, is reduced significantly, which together with the very low treatment probabilities questions the validity of the IV results for the sample of the younger age group, as weak instruments possibly introduce a bias similar to or stronger than the potential bias in the probit estimates (Staiger et al., 1997). We therefore additionally apply a method proposed by Lewbel (2012), which uses heteroscedasticity in the estimated models to construct additional instruments. Instruments are generated by multiplying the heteroscedastic residuals from the first-stage regressions with a subset of the included exogenous variables. Lewbel (2012) recommends the use of this method when traditional instruments are not available or if it is suspected that the traditional instrument is too weak for identification, which is the issue at hand. The approach has been widely used over the last years both in health economics (Brown, 2014; Drichoutis et al., 2011; Kelly et al., 2014; Schroeter et al., 2012) and in other economic disciplines (Denny et al., 2013; Emran et al., 2012; Huang et al., 2009). Using this method to construct additional instruments by using our age group dummies, we are able to increase instrument strength significantly in the younger age group and the overidentification test indicates validity of the instruments. The results of the linear IV model with the additional instruments show exogeneity of diabetes for males and females and do not indicate a significant positive effect of diabetes on employment probabilities.

Apart from the results of the Lewbel approach, we also think that there are theoretical reasons why diabetes is likely exogenous in the younger age group. While we cannot distinguish between the types of diabetes with the data at hand, it is likely that a relatively large proportion of the people reporting diabetes in this age group have type 1 diabetes, which people tend to get at a younger age (Maahs et al., 2010). The disease has a strong genetic component and it is very unlikely that there are unobserved factors that affect the chances to develop type 1 diabetes and being employed at the same time, nor that employment status would affect the development of type 1 diabetes. Therefore, for a large part of the people reporting diabetes in the younger age group, endogeneity should not present a problem because they have type 1 diabetes. Furthermore, it is also less

likely that reverse causality is a problem for those having type 2 diabetes in this age group, because any effects of being employed on developing type 2 diabetes take time to develop. It would be reasonable to expect that if being employed affected a person's weight or any other diabetes risk factor, this would happen by changing the person's lifestyle due to changes in income or available leisure time, or by reducing or increasing a person's activity levels at work. Until these changes are expressed in changes in weight or any other risk factor for diabetes and finally cause a development of type 2 diabetes, a considerable time period of various years has likely passed and people have reached an advanced age. We therefore believe, that the risk of diabetes being affected by employment is much lower in the younger age group based on the nature of the disease, compared to the older age group. Hence we think that the assumption of exogeneity of diabetes in the younger age group is valid—which is also supported by the Lewbel estimates—and that the endogeneity indicated for younger females in the bivariate probit model is likely the result of the low prevalence rates, and consequently the very low treatment probabilities, together with weak instruments, making a meaningful IV analysis difficult (Chiburis et al., 2012). We are therefore confident that we can rely on our probit estimates for inference.

Table A7: IV estimates for the age group 15–44

	BP		Lewbel IV	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	0.171***	0.496***	0.007	0.051
	(.046)	(.080)	(.053)	(.071)
R2			0.093	0.143
Score goodness-of-fit (H0=normality of errors)	9.56	14.25		
p value	0.387	0.114		
F stat (H0: weak instruments)	4.288[a]	10.835[a]	366.480	65.872
Sargan test (H0: valid instruments)	0.008[a]	0.044[a]	1.817	3.487
p value	0.930[a]	0.834[a]	0.611	0.322
Endogeneity (H0: Diabetes exogenous)	1.422	12.948	1.065	1.429
p value	0.233	0.000	0.302	0.232
N	4415	5997	4415	5997

Notes Average marginal effects for bivariate probit (BP); robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father; for Lewbel additionally created age groups instruments. The models contain the age categories 25–34 and 35–44 with 15–24 as the reference category. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. [a] The test statistics are taken from the linear IV model not presented here. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: IV estimates for the age group 45–64

	BP		Lewbel IV	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	−.022	−.112	−.178	−.042
	(.138)	(.111)	(.160)	(.104)
R2			0.058	0.118
Score goodness-of-fit (H0=normality of errors)	7.00	11.10		
p value	0.637	0.269		
F stat. (H0: weak instruments)	15.408[a]	18.305[a]	12.534	18.897
Sargan test (H0: valid instruments)	2.717[a]	0.482[a]	4.397	1.688
p value	0.067[a]	0.487[a]	0.111	0.430
Endogeneity (H0: Diabetes exogenous)	0.688	0.574	0.082	0.024
p value	0.407	0.449	0.774	0.876
N	1871	2246	1871	2246

Notes Average marginal effects for bivariate probit (BP); robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father; for Lewbel additionally created age groups instruments. The models contain the age categories 55–64 with 45–54 as the reference category. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. [a] The test statistics are taken from the linear IV model not presented here. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results for wealth quartiles

Table A9: Impact of diabetes on employment probabilities by wealth quartile (probit)

	1st		2nd		3rd		4th	
	(1) Males	(2) Females	(3) Males	(4) Females	(5) Males	(6) Females	(7) Males	(8) Females
Diabetes	−.142*	−.101***	−.144**	0.028	−.082	−.026	−.040	−.053
	(.077)	(.029)	(.060)	(.048)	(.053)	(.044)	(.046)	(.048)
Log likelihood	−776.619	−937.144	−672.633	−1092.280	−689.910	−1266.304	−703.495	−1144.588
N	1577	2039	1563	2052	1516	2143	1590	1974

Notes Average marginal effects; robust standard errors in parentheses. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Instrumental variable analysis for wealth groups

To consider the possible endogeneity of diabetes in the upper and lower wealth half, we again present the results of the bivariate probit and the Lewbel model. The stratification into wealth groups significantly reduces instrument power as well as sample size. For none of the wealth groups the bivariate probit model indicates endogeneity (see Table A10 and Table A11 in the appendix). This does not change even when using the Lewbel approach to increase instrument strength. Accordingly, we do not find any indication of endogeneity of diabetes in the wealth groups and rely on our probit estimates for inference.

Table A10: IV results for lower wealth half

	BP		Lewbel IV	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	−.354	−.064	−.142***	−.054*
	(.241)	(.139)	(.050)	(.032)
R2			0.071	0.099
Score goodness-of-fit (H0=normality of errors)	NA[a]	7.41		
p value	NA[a]	0.594		
F stat (H0: weak instruments)	6.322[b]	15.420[b]	2589.091	1311.647
Sargan test (H0: valid instruments)	0.342[b]	1.106[b]	4.169	2.804
p value	0.558[b]	0.293[b]	0.525	0.730
Endogeneity (H0: Diabetes exogenous)	1.190	0.016	0.005	0.156
p value	0.275	0.901	0.941	0.693
N	3169	4111	3169	4111

Notes Average marginal effects for bivariate probit (BP); robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father; for Lewbel additionally created age groups instruments. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. [a] The test statistics are taken from the linear IV model not presented here. The command SCOREGOF failed to produce the test statistic for this subsample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: IV results for upper wealth half

	BP		Lewbel IV	
	(1) Males	(2) Females	(3) Males	(4) Females
Diabetes	−.142	0.103	−.057	−.000
	(.199)	(.203)	(.037)	(.039)
R2			0.089	0.142
Score goodness-of-fit (H0=normality of errors)	11.40	12.92		
p value	0.249	0.166		
F stat (H0: weak instruments)	14.003[a]	13.215[a]	28673.088	1225.456
Sargan test (H0: valid instruments)	0.848[a]	0.019[a]	10.180	5.787
p value	0.357[a]	0.889[a]	0.070	0.327
Endogeneity (H0: Diabetes exogenous)	0.238	0.730	0.955	1.807
p value	0.626	0.393	0.329	0.179
N	3117	4132	3117	4132

Notes Average marginal effects for bivariate probit (BP); robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father; for Lewbel additionally created age groups instruments. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. [a] The test statistics are taken from the linear IV model not presented here. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Multinomial logit and IV results for formal and informal employment

Table A12: Impact of diabetes on employment probabilities by employment status (multinomial logit)

	Males		Females	
	(1) Informal	(2) Formal	(3) Informal	(4) Formal
Diabetes	−.073**	0.031	−.044**	0.008
	(.031)	(.026)	(.019)	(.018)
Log likelihood	−4997.064	−4997.064	−6267.941	−6267.941
N	6286	6286	8243	8243

Notes Average marginal effects. Base category is being unemployed. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To consider the possible endogeneity of diabetes when estimating its effect on formal and informal employment, we again present the results of the bivariate probit and the Lewbel model. The stratification into formal and informal employment groups significantly reduces instrument power as well as sample size. For none of the employment groups the bivariate probit model indicates endogeneity (see Table A13 and Table A14 in the appendix). This does not change even when using the Lewbel approach to increase instrument strength. Accordingly, we do not find any indication of endogeneity of diabetes for the stratification into formal and informal employment and rely on our probit estimates for inference.

Table A13: IV results for informal employment

	BP		Lewbel IV	
	(1) Male	(2) Female	(3) Male	(4) Female
Diabetes	−.046	0.069	−.048	−.037
	(.123)	(.130)	(.030)	(.025)
R2			0.103	0.088
Score goodness-of-fit (H0=normality of errors)	13.84	17.37		
p value	0.128	0.043		
F stat (H0: weak instruments)	13.565[a]	25.123[a]	5349.118	2536.362
Sargan test (H0: valid instruments)	0.551[a]	1.684[a]	4.067	4.063
p value	0.458[a]	0.194[a]	0.540	0.540
Endogeneity (H0: Diabetes exogenous)	0.025	1.152	1.128	0.722
p value	0.873	0.283	0.288	0.395
N	4604	6983	4604	6983

Notes Average marginal effects for bivariate probit (BP); robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father; for Lewbel additionally created age groups instruments. The models contain the age categories 55–64 with 45–54 as the reference category. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. [a] The test statistics are taken from the linear IV model not presented here. Base category is being unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: IV results for formal employment

	BP		Lewbel IV	
	(1) Male	(2) Female	(3) Male	(4) Female
Diabetes	0.098	−.103	−.022	0.003
	(.195)	(.069)	(.049)	(.021)
R2			0.256	0.262
Score goodness-of-fit (H0=normality of errors)	12.95	8.03		
p value	0.165	0.531		
F stat (H0: weak instruments)	8.518[a]	19.996[a]	2764.273	1647.887
Sargan test (H0: valid instruments)	1.111[a]	1.075[a]	9.286	6.741
p value	0.292[a]	0.300[a]	0.098	0.241
Endogeneity (H0: Diabetes exogenous)	0.516	1.833	1.602	0.318
p value	0.473	0.176	0.206	0.573
N	2204	5652	2204	5652

Notes Average marginal effects for bivariate probit (BP); robust standard errors in parentheses. Instruments: diabetes of mother, diabetes of father; for Lewbel additionally created age groups instruments. The models contain the age categories 55–64 with 45–54 as the reference category. Other control variables: region, urban, education, indigenous, marital status, children, wealth, parental education. [a] The test statistics are taken from the linear IV model not presented here. Base category is being unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IV Appendix to Chapter 4

Strategies to deal with inconsistent self-reporting over time

One of the key advantages of panel data is the repeated measurement giving more than one data point for many of the individuals, thereby allowing to uncover inconsistencies for those with at least two observations. While we are not aware of any literature investigating the issue of inconsistencies in self-reported diabetes over time, a study by Zajacova et al. (2010), on the consistency of a self-reported cancer diagnosis over time in a USA population, found that 30% of those who had reported a cancer diagnosis at an earlier point did report at a later point that they never had received a cancer diagnosis. They also found that a more recent diagnosis was reported with greater consistency possibly due to increasing recall problems and/or reduced salience as time since diagnosis progresses.

We also find inconsistencies in the diabetes self-reports over the three waves of the Mexican Family Life Survey (MxFLS) data, with between 10%–20% of those reporting diabetes in one wave not doing so in one of the subsequent waves. In order to reduce the amount of inconsistencies, we were interested in the validity of diabetes self-reports. While we could not find a study assessing the validity of self-reported diabetes in Mexico, a study from China has shown that specificity of self-reported diabetes, i.e. those who self-report a diabetes diagnosis actually have diabetes, was very high (>98% for China), while sensitivity, i.e. how many people with diabetes, diagnosed or undiagnosed, actually self-report the disease, was low (40% for China) (Yuan et al., 2015). This indicates that people who report a diabetes diagnosis are likely to indeed have the condition while many of those not reporting a diabetes diagnosis are unaware of their diabetes.

We assess the validity of self-reported diabetes in our data by using HbA1c levels and the self-reports of diabetes related medicine use from wave three. We find that 90% of those self-reporting a diabetes diagnosis had an HbA1c $\geq 6.5\%$ or did report taking diabetes medication, indicating relatively high specificity in our data as well.

We used this information to infer the "true" diabetes status for those with inconsistent reports. For those with two waves, we assumed that if a diabetes diagnosis had been reported in a prior wave they also had diabetes in the ensuing wave, even if then it was not reported. For people where we had data from all

three waves, we used that additional information to make a decision on how to deal with inconsistencies using the rules outlined in Table A15 in the appendix.

This approach should add more consistency to the self-reported diabetes information by using all available information. We tested if this approach was supported by the HbA1c values provided in wave 3. Of those with inconsistencies in their diabetes self-reports 95 were present in the biomarker sample (46 with two and 49 with one self-report of diabetes). Using a t-test we compared the mean HbA1c for the two groups and found a significantly ($p<0.001$) higher mean HbA1c (9.7) for those with two self-reports compared to for those with only one self-report of diabetes (7.0). Further, of those with one self-report, for only 30% the HbA1c ≥ 6.5 compared to 87% of those with two self-reports. Based on these results we are reassured that the way we have dealt with the inconsistencies in the data minimizes misclassification of people into diabetes or no-diabetes and has reduced some of the measurement error in the diabetes data. Unfortunately we cannot use a similar method for dealing with inconsistencies in the self-reported year of diabetes diagnosis, as it has only been reported once. Hence, the results from duration analysis should be interpreted with care.

Table A15: Inconsistencies in diabetes self-report in MxFLS

Diabetes self-report			Assumption	Number of observations replaced
2002	2005	2009		
Yes	Yes	No	Has diabetes in 2009 as well	19
Yes	No	Yes	Has diabetes in 2005 as well	63
Yes	No	No	Has no diabetes in 2002 either	66
No	Yes	No	Has no diabetes in 2005 either	52
Yes	No	NA	Has diabetes in 2005 as well	44
NA	Yes	No	Has diabetes in 2009 as well	23

V Appendix to Chapter 5

Attrition

Table A16: Attrition between waves

1997–2000	11.9%
2000–2004	13.0%
2004–2006	8.3%
2006–2009	16.2%
2009–2011	16.7%
Total	10.6%

Missing data

Table A17: Number of imputed observations

Variable	Missing	Total	Missing (%)
Employed	2333	47661	4.89
Smokes	3315	47661	6.96
Any alcohol consumption	3438	47661	7.21
Daily Kcal eaten (3-day average)	3599	47661	7.55
BMI	6092	47661	12.78
Waist circ. (cm)	6361	47661	13.35
Age	0	47661	0.00
Han ethnicity	0	47661	0.00
Rural area	0	47661	0.00
Married	2625	47661	5.51
Secondary education	254	47661	5.33
University education	254	47661	5.33
Any health insurance	253	47661	5.31
Urbanization Index	0	47661	0.00
Diabetes	0	47661	0.00
Per capita household income (Yuan (2011))	552	47661	1.16
Years since diabetes diagnosis	333	47661	0.70

Stabilized weights

Table A18: Summary of stabilized weights

	Mean	Min	Max
Untruncated (men)	1.000515	0.281853	2.642838
Untruncated (women)	0.999907	0.451526	2.053581
Truncated 1 and 99 percentile (men)	0.999756	0.945491	1.057514
Truncated 1 and 99 percentile (women)	1.000001	0.960039	1.049472
Using overweight and obesity instead of BMI and waist circumference			
Untruncated (men)	1.000516	0.232143	2.592925
Untruncated (women)	0.999857	0.251297	2.491703
Truncated 1 and 99 percentile (men)	0.999794	0.944632	1.058910
Truncated 1 and 99 percentile (women)	0.999782	0.932321	1.077095

Duration groups results

Table A19: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using marginal structural models (duration groups)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.088	−.031	0.049	−1.138**	−.728	278.504
	(.059)	(.122)	(.147)	(.530)	(1.927)	(301.190)
1-2	0.024	−.049	−.102**	−.485*	−1.261	−133.527
	(.034)	(.042)	(.040)	(.260)	(.876)	(96.402)
3-4	−.033	−.091	−.082*	−.665**	−2.505***	−160.612*
	(.042)	(.056)	(.045)	(.309)	(.814)	(84.241)
5-6	−.110	−.116	−.090	−.917**	−1.009	−156.064
	(.068)	(.080)	(.056)	(.384)	(.980)	(117.322)
7-8	0.044	−.191	−.146*	−.833*	−1.590	−260.923**
	(.076)	(.134)	(.079)	(.467)	(2.276)	(130.336)
9-10	−.052	−.040	0.197	−2.198***	−6.075**	−386.292*
	(.117)	(.140)	(.181)	(.765)	(2.591)	(199.311)
11-12	0.013	−.001	−.165	−.881	−3.505	40.936
	(.120)	(.132)	(.125)	(.708)	(2.522)	(174.858)
13-14	0.004					
	(.124)					
Female sample						
0	0.078			0.099	−1.210	−59.570
	(.139)			(1.021)	(3.866)	(157.723)
1-2	−.085**			−.191	−.303	−32.947
	(.040)			(.352)	(.724)	(50.797)
3-4	−.202***			−.411	0.591	−21.502
	(.067)			(.461)	(1.232)	(62.460)
5-6	−.070			−.475	−.187	−53.234
	(.066)			(.337)	(1.055)	(61.737)
7-8	−.180**			−1.049**	−1.787*	−94.532
	(.088)			(.426)	(1.057)	(105.698)
9-10	−.329*			−1.054	0.324	66.951
	(.168)			(.822)	(2.538)	(125.902)
11-12	−.119			−.554	−3.906	−29.022
	(.120)			(1.089)	(2.464)	(152.223)
13-14	−.117					
	(.154)					

Notes The coefficients for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. The smoking and alcohol models for females could not be estimated due to too few non-zero observations. Similarly, apart from the employment models, the years 13-14 had to be omitted due to too few observations for theses years. Other control variables: baseline values of age, age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using fixed effects (duration groups)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.151**	−.005	0.027	0.064	2.200	−112.476
	(.072)	(.097)	(.161)	(.822)	(2.257)	(232.264)
1-2	0.040	−.029	−.137***	−.598***	−1.714**	−228.738***
	(.038)	(.038)	(.042)	(.230)	(.784)	(85.913)
3-4	0.010	−.007	−.066	−.706**	−2.992***	−113.409
	(.044)	(.051)	(.050)	(.296)	(.797)	(86.909)
5-6	−.118	−.026	−.093	−1.164***	−2.191*	−22.369
	(.079)	(.072)	(.062)	(.341)	(1.309)	(112.692)
7-8	0.126	−.147	−.262**	−.750	−3.009	−302.744**
	(.078)	(.120)	(.116)	(.493)	(1.886)	(131.910)
9-10	0.036	0.004	0.054	−2.123***	−7.756***	−228.356
	(.141)	(.138)	(.145)	(.788)	(2.799)	(184.833)
11-12	0.066	−.042	−.256*	−1.604**	−6.693**	−195.061
	(.180)	(.156)	(.141)	(.742)	(3.094)	(160.761)
13-14	0.042	0.186	−.218	−1.389	−4.626***	−167.675
	(.183)	(.126)	(.140)	(1.168)	(1.190)	(147.716)
Female sample						
0	0.102	−.015**	−.035	−.468	−4.036	−322.767*
	(.157)	(.007)	(.032)	(.884)	(3.229)	(171.460)
1-2	−.104***	−.031**	−.019*	−.419	−.727	−98.608*
	(.034)	(.013)	(.011)	(.349)	(.683)	(56.443)
3-4	−.110**	−.022	−.012	−.756**	−.896	42.743
	(.056)	(.015)	(.016)	(.378)	(1.000)	(67.154)
5-6	−.095	−.049	0.007	−1.012***	−2.293**	−49.270
	(.072)	(.038)	(.018)	(.309)	(1.021)	(84.604)
7-8	−.219**	0.014	−.000	−1.385***	−3.238***	−76.316
	(.090)	(.032)	(.013)	(.391)	(.962)	(102.021)
9-10	−.261**	0.024	−.001	−.794	−.240	−12.562
	(.124)	(.035)	(.025)	(.572)	(2.056)	(134.903)
11-12	−.209*	−.070	−.002	−.676	−4.068*	−2.327
	(.111)	(.053)	(.009)	(.973)	(2.462)	(152.643)
13-14	−.178	−.026	−.001	−.001	0.056	−301.362***
	(.164)	(.018)	(.027)	(.708)	(2.411)	(94.674)

Notes All estimates are beta coefficients from linear regression models. Other control variables: age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=23443 (male sample), N=23702 (female sample). * $p < 0.10$, ** $p < 0.05$, ***. $p < 0.01$

Table A21: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using random effects (duration groups)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.123*	−.034	0.051	0.381	3.652*	2.069
	(.068)	(.097)	(.150)	(.707)	(2.075)	(203.971)
1-2	−.005	−.067*	−.142***	−.276	−.392	−223.036***
	(.038)	(.037)	(.036)	(.224)	(.766)	(78.475)
3-4	−.048	−.052	−.081*	−.316	−1.318*	−155.191**
	(.044)	(.048)	(.045)	(.304)	(.769)	(72.913)
5-6	−.133*	−.071	−.084	−.759**	−.403	−75.706
	(.076)	(.069)	(.058)	(.344)	(1.148)	(104.001)
7-8	0.093	−.208*	−.194*	−.434	−1.172	−272.523**
	(.075)	(.112)	(.102)	(.485)	(1.703)	(109.241)
9-10	−.018	−.028	0.122	−1.804**	−5.786**	−234.745
	(.142)	(.134)	(.142)	(.749)	(2.609)	(166.358)
11-12	0.012	−.071	−.209	−1.360*	−5.108*	−90.369
	(.166)	(.160)	(.132)	(.726)	(2.790)	(158.103)
13-14	0.008	0.206**	−.152	−.985	−2.776**	−14.049
	(.157)	(.093)	(.142)	(1.225)	(1.122)	(101.033)
Female sample						
0	0.034	0.003	−.035**	0.097	−1.037	−145.397
	(.145)	(.025)	(.017)	(.842)	(3.375)	(139.781)
1-2	−.135***	−.028***	−.026***	−.025	0.857	−44.182
	(.031)	(.011)	(.004)	(.337)	(.631)	(52.022)
3-4	−.169***	−.018	−.015	−.379	0.901	−3.834
	(.049)	(.014)	(.014)	(.372)	(1.005)	(57.700)
5-6	−.129**	−.038	−.005	−.612**	−.317	−43.769
	(.063)	(.033)	(.018)	(.305)	(.992)	(69.632)
7-8	−.225***	0.024	−.018*	−1.015***	−1.357	−69.287
	(.075)	(.034)	(.010)	(.377)	(.908)	(105.179)
9-10	−.286**	0.026	−.018	−.515	1.421	98.605
	(.111)	(.042)	(.024)	(.572)	(1.937)	(127.672)
11-12	−.195*	−.060	−.020***	−.265	−2.043	31.945
	(.117)	(.043)	(.005)	(.948)	(2.622)	(137.113)
13-14	−.152	−.022*	−.018	0.503	2.325	−301.291***
	(.152)	(.013)	(.026)	(.773)	(2.541)	(91.369)

Notes All outcomes are beta coefficients from linear regression models.Other control variables: age, age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=23443 (male sample), N=23702 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness checks

MSMs using truncated weights

Table A22: Analysis of the effect of a diabetes diagnosis on employment status and behavioural outcomes using marginal structural models with truncated stabilized weights at 1st and 99th percentile

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
			Diabetes			
Male sample						
Diabetes	−.022	−.070**	−.094***	−.732***	−1.637***	−175.662***
	(.023)	(.032)	(.036)	(.179)	(.532)	(51.574)
Female sample						
Diabetes	−.132***	−.015*	−.029**	−.178	0.186	−47.980
	(.029)	(.008)	(.012)	(.248)	(.638)	(34.319)
			Years since diagnosis			
Male sample						
Time since diagnosis	−.006	−.010**	−.016**	−.133***	−.326***	−26.261***
	(.004)	(.005)	(.006)	(.033)	(.095)	(9.160)
Female sample						
Time since diagnosis	−.019***	−.002	−.004	−.044	−.016	−9.096
	(.006)	(.001)	(.003)	(.042)	(.112)	(5.681)

Notes The coefficients for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. Other control variables: baseline values of age, age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Effect of time since diagnosis on employment status and behavioural outcomes using MSM with truncated stabilized weights (1st and 99th percentile; imputed), duration groups

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.089	−.047	0.031	−1.107**	−.326	83.518
	(.061)	(.135)	(.143)	(.522)	(1.909)	(236.282)
1-2	−.002	−.072*	−.121***	−.472*	−.962	−197.071**
	(.034)	(.041)	(.033)	(.254)	(.843)	(82.739)
3-4	−.042	−.073	−.088**	−.654**	−2.113***	−189.546**
	(.038)	(.050)	(.040)	(.299)	(.693)	(77.787)
5-6	−.107*	−.091	−.094*	−1.022***	−.954	−151.346
	(.063)	(.074)	(.053)	(.360)	(1.013)	(107.678)
7-8	0.054	−.222*	−.127	−.863*	−2.157	−264.374**
	(.063)	(.118)	(.078)	(.462)	(2.034)	(115.620)
9-10	−.075	−.024	0.122	−2.270***	−5.774**	−289.988*
	(.117)	(.136)	(.148)	(.700)	(2.424)	(174.301)
11-12	−.024	−.028	−.167	−.888	−3.275	−8.651
	(.126)	(.127)	(.112)	(.713)	(2.467)	(163.025)
13-14	−.053					
	(.142)					
Female sample						
0	0.068			0.541	0.219	−102.210
	(.134)			(1.136)	(4.359)	(139.467)
1-2	−.114***			0.130	0.472	−28.298
	(.040)			(.359)	(.723)	(53.113)
3-4	−.208***			−.298	0.866	−31.300
	(.064)			(.457)	(1.193)	(61.496)
5-6	−.097			−.319	0.103	−60.088
	(.063)			(.347)	(1.084)	(66.056)
7-8	−.184**			−.979**	−1.522	−94.059
	(.089)			(.449)	(1.074)	(107.062)
9-10	−.344**			−.975	0.637	71.060
	(.168)			(.827)	(2.541)	(133.178)
11-12	−.119			−.432	−3.355	−12.232
	(.113)			(1.070)	(2.603)	(141.560)
13-14	−.106					
	(.152)					

Notes The coefficients for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. The smoking and alcohol models for females could not be estimated due to too few non-zero observations. Similarly, apart from the employment models, the years 13-14 had to be omitted due to too few observations for theses years. Other control variables: baseline values of age, age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results using non-imputed data

Table A24: Analysis of the effect of a diabetes diagnosis on employment status and behavioural outcomes using MSM, FE and RE (no imputation)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
			Marginal structural model			
Male sample						
Diabetes	0.049	−.054	−.118**	−.601***	−1.290	−205.746*
	(.043)	(.040)	(.053)	(.229)	(.859)	(109.375)
Female sample						
Diabetes	−.087*	−.026*	0.000	−.637	−1.043	−45.166
	(.047)	(.016)	(.)	(.402)	(.865)	(56.543)
			Fixed effects			
Male sample						
Diabetes	0.024	−.004	−.103***	−.844***	−2.463***	−152.316**
	(.030)	(.033)	(.036)	(.169)	(.508)	(67.898)
Female sample						
Diabetes	−.110***	−.024**	−.015	−.634**	−1.105*	−81.340*
	(.034)	(.012)	(.012)	(.288)	(.636)	(49.016)
			Random effects			
Male sample						
Diabetes	−.023	−.045	−.109***	−.569***	−1.163**	−143.470***
	(.027)	(.030)	(.029)	(.166)	(.482)	(51.625)
Female sample						
Diabetes	−.164***	−.020**	−.021***	−.309	0.494	−59.269*
	(.026)	(.009)	(.005)	(.269)	(.583)	(35.037)
			Robust Hausman test of fixed effects vs. random effects			
Male sample						
Chi^2	449.597	230.700	99.211	299.581	230.399	51.810
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Female sample						
Chi^2	337.522	52.231	27.422	251.371	149.501	51.005
p-value	<0.001	<0.001	0.017	<0.001	<0.001	<0.001

Notes The coefficients of the MSM for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. Other control variables for FE/RE: age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. RE additionally controls for age. MSM controls for baseline values of the same variables as the FE/RE models additionally to baseline values of age, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. FE/RE: N=22135 (male sample), N=23143 (female sample), MSM: N=10006 (male sample), N=11471 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A25: Analysis of the effect of each year since diabetes diagnosis on employment status and behavioural outcomes using MSM, FE and RE (non-imputed)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
			Marginal structural model			
Male sample						
Time since diagnosis	0.019	−.019	−.036*	−.203**	−.550*	−85.203**
	(.017)	(.015)	(.022)	(.081)	(.310)	(38.378)
Female sample						
Time since diagnosis	−.028	−.008	0.000	−.338*	−.579*	−14.298
	(.017)	(.006)	(.)	(.178)	(.333)	(21.193)
			Fixed effects			
Male sample						
Time since diagnosis	−.001	0.003	−.016**	−.158***	−.516***	−18.202
	(.007)	(.006)	(.007)	(.039)	(.118)	(12.059)
Female sample						
Time since diagnosis	−.023***	−.002	−.001	−.103**	−.177	−9.987
	(.008)	(.002)	(.001)	(.045)	(.127)	(7.788)
			Random effects			
Male sample						
Time since diagnosis	−.007	−.003	−.015***	−.120***	−.317***	−20.749**
	(.006)	(.006)	(.006)	(.038)	(.101)	(9.382)
Female sample						
Time since diagnosis	−.026***	−.002	−.003***	−.065	0.043	−7.041
	(.006)	(.002)	(.001)	(.044)	(.124)	(6.479)

Notes The coefficients of the MSM for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. Other control variables for FE/RE: age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. RE additionally controls for age. MSM controls for baseline values of the same variables as the FE/RE models additionally to baseline values of age, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. FE/RE: N=22117 (male sample), N=23130 (female sample), MSM: N=10028 (male sample), N=11465 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A26: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using marginal structural models (duration groups) (non-imputed)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.119*	0.053	0.010	−.942	0.596	459.443
	(.070)	(.170)	(.156)	(.589)	(.934)	(474.665)
1-2	0.026	−.055	−.137***	−.571**	−1.270	−182.199
	(.044)	(.046)	(.043)	(.273)	(1.040)	(121.087)
3-4		−.043	0.131	−1.013**	−3.347	−782.090***
		(.153)	(.156)	(.450)	(2.116)	(177.206)
Female sample						
0	0.123			−.136	−1.772	−101.086
	(.188)			(1.488)	(5.608)	(203.293)
1-2	−.083			−.613	−.685	−40.447
	(.067)			(.489)	(1.026)	(65.853)
3-4				−5.530*	−8.510***	0.676
				(3.260)	(1.787)	(257.875)

Notes The coefficients for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. The number of year groups is limited due to too few observations for estimation within each group. Other control variables: baseline values of age, age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures, alcohol consumption, smoking status, BMI, waist circumference and calorie consumption. N=10028 (male sample), N=11465 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A27: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using fixed effects (duration groups) (non-imputed)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.126*	−.013	0.081	−.013	1.444	−268.541
	(.073)	(.084)	(.156)	(.704)	(1.883)	(213.448)
1-2	0.046	−.019	−.135***	−.817***	−2.298***	−225.905**
	(.039)	(.039)	(.042)	(.199)	(.637)	(90.437)
3-4	0.013	0.035	−.052	−.786**	−3.016***	−107.317
	(.046)	(.054)	(.055)	(.325)	(.819)	(98.624)
5-6	−.134*	0.028	−.134**	−1.159***	−1.715	34.167
	(.079)	(.077)	(.065)	(.343)	(1.178)	(117.774)
7-8	0.162**	−.138	−.270**	−.692	−2.555	−305.553**
	(.078)	(.117)	(.117)	(.429)	(1.726)	(133.202)
9-10	−.018	0.044	0.082	−1.938***	−8.278***	−196.802
	(.136)	(.123)	(.131)	(.667)	(2.262)	(201.492)
11-12	0.063	0.089	−.177**	−1.743**	−5.843**	−22.708
	(.178)	(.134)	(.082)	(.736)	(2.828)	(140.771)
13-14	0.060	0.222**	−.164	−1.508	−4.207***	−119.852
	(.194)	(.113)	(.111)	(1.202)	(1.063)	(178.187)
Female sample						
0	0.101	−.014**	−.046	−.778	−3.920	−358.037**
	(.154)	(.007)	(.040)	(.909)	(3.420)	(173.529)
1-2	−.100***	−.029**	−.023*	−.329	−.558	−118.162**
	(.033)	(.012)	(.012)	(.363)	(.671)	(56.839)
3-4	−.148**	−.017	−.025*	−.822*	−.824	49.550
	(.059)	(.013)	(.014)	(.442)	(1.148)	(82.984)
5-6	−.122*	−.043	0.002	−1.028***	−1.616	−69.012
	(.073)	(.041)	(.020)	(.325)	(1.016)	(96.779)
7-8	−.235***	0.023	−.004	−1.327***	−3.174***	−90.185
	(.090)	(.027)	(.008)	(.390)	(.978)	(111.004)
9-10	−.247**	0.031	−.010	−.981	−.260	−64.808
	(.118)	(.039)	(.009)	(.621)	(2.131)	(134.146)
11-12	−.239**	−.070	−.005	−.715	−3.440	−25.527
	(.103)	(.056)	(.009)	(1.021)	(2.512)	(173.367)
13-14	−.199	−.023	−.008	−.111	0.693	−366.259***
	(.166)	(.018)	(.009)	(.665)	(2.153)	(87.213)

Notes Linear regression coefficients. Robust standard errors in parentheses. Other control variables: age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=22117 (male sample), N=23130 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A28: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using random effects (duration groups) (non-imputed)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.094	−.043	0.065	0.148	2.276	−28.615
	(.069)	(.087)	(.144)	(.610)	(1.683)	(188.201)
1-2	−.008	−.053	−.144***	−.533***	−1.045	−203.986**
	(.038)	(.038)	(.036)	(.195)	(.658)	(80.054)
3-4	−.041	−.007	−.070	−.493	−1.730**	−140.623
	(.045)	(.051)	(.051)	(.336)	(.809)	(87.834)
5-6	−.159**	−.012	−.120**	−.866***	−.330	−69.752
	(.077)	(.073)	(.060)	(.333)	(1.054)	(115.094)
7-8	0.114	−.213**	−.215**	−.473	−1.072	−243.936**
	(.074)	(.108)	(.097)	(.431)	(1.538)	(105.320)
9-10	−.070	0.001	0.127	−1.803***	−7.021***	−173.366
	(.134)	(.118)	(.132)	(.620)	(2.127)	(167.349)
11-12	0.005	0.060	−.160	−1.446*	−4.339	92.244
	(.159)	(.144)	(.100)	(.767)	(2.681)	(148.282)
13-14	0.029	0.234***	−.118	−1.101	−2.531***	38.227
	(.161)	(.083)	(.128)	(1.263)	(.931)	(100.439)
Female sample						
0	0.025	0.003	−.039**	−.238	−1.178	−123.300
	(.145)	(.025)	(.016)	(.874)	(3.554)	(139.671)
1-2	−.142***	−.028***	−.028***	0.001	0.848	−66.418
	(.031)	(.010)	(.004)	(.349)	(.622)	(49.483)
3-4	−.195***	−.020*	−.028***	−.481	1.064	43.196
	(.052)	(.012)	(.005)	(.433)	(1.090)	(68.580)
5-6	−.159**	−.034	−.007	−.647**	0.445	−52.781
	(.063)	(.035)	(.021)	(.315)	(.981)	(77.715)
7-8	−.247***	0.029	−.022***	−1.073***	−1.501*	−90.408
	(.070)	(.031)	(.003)	(.368)	(.886)	(116.975)
9-10	−.286***	0.029	−.024***	−.748	1.422	124.263
	(.099)	(.046)	(.003)	(.605)	(1.900)	(156.687)
11-12	−.214*	−.062	−.022***	−.335	−1.482	49.789
	(.114)	(.046)	(.005)	(1.000)	(2.752)	(155.171)
13-14	−.176	−.022*	−.024***	0.298	2.665	−332.344***
	(.153)	(.012)	(.006)	(.755)	(2.407)	(99.899)

Notes Linear regression coefficients. Robust standard errors in parentheses. Other control variables: age, age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=22117 (male sample), N=23130 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Overweight and obesity results

Table A29: Analysis of the effect of a diabetes diagnosis on overweight and obesity using MSM, FE and RE

	Males		Females	
	(1) Overweight	(2) Obese	(3) Overweight	(4) Obese
	Marginal structural model			
Diabetes	−.000	−.024	−.031	−.009
	(.031)	(.015)	(.034)	(.014)
	Fixed Effects			
Diabetes	−.041	−.035	−.095***	−.034
	(.035)	(.025)	(.036)	(.027)
	Random Effects			
Diabetes	0.014	−.006	−.070**	0.028
	(.030)	(.023)	(.030)	(.024)

Notes The coefficients for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. Other control variables for FE/RE: age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. RE additionally controls for age. MSM controls for baseline values of the same variables as the FE/RE models additionally to baseline values of age, alcohol consumption, smoking status, overweight status, obesity status and calorie consumption. FE/RE: N=23443 (male sample), N=23702 (female sample). MSM: N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A30: Analysis of the effect of time since diagnosis on overweight and obesity using MSM, FE, RE

	Males		Females	
	(1) Overweight	(2) Obese	(3) Overweight	(4) Obese
	Marginal structural model			
Time since diagnosis	−.001	−.005*	−.003	−.003
	(.005)	(.003)	(.005)	(.002)
	Fixed Effects			
Time since diagnosis	−.006	−.007*	−.006	−.009*
	(.007)	(.004)	(.006)	(.005)
	Random Effects			
Time since diagnosis	0.002	−.003	−.006	−.001
	(.006)	(.003)	(.005)	(.004)

Notes The coefficients for outcomes 1–3 represent average marginal effects based on logistic regression models. All other coefficients are from linear regression models. Robust standard errors in parentheses. Other control variables for FE/RE: age squared, region, urban, education, Han ethnicity, marital status, urbanization index, time dummies, health insurance status, household expenditures. RE additionally controls for age. MSM controls for baseline values of the same variables as the FE/RE models additionally to baseline values of age, alcohol consumption, smoking status, overweight status, obesity status and calorie consumption. FE/RE: N=23443 (male sample), N=23702 (female sample). MSM: N=16047 (male sample), N=16658 (female sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Analysis of the effect of time since diabetes diagnosis on overweight and obesity (duration groups)