Thesis submitted for the degree of Doctor of Philosophy (PhD)

The Economics of Diabetes in Middle-Income-Countries

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Abstract

This thesis focuses on the economic analysis of type 2 diabetes in **MIC!**s (**MIC!**s). Given its rising prevalence, in-depth country specific analysis is key for understanding the economic consequences of T2D in **MIC!**s. I analyse the economic burden of type 2 diabetes in terms of labour market consequences, taking into account the heterogeneity of the diabetes population, for both Mexico and China. For China I further investigate the effects of a diabetes diagnosis on health behaviours.

The thesis consists of four studies with the unifying theme of improving our understanding of the causal relationship between diabetes and economic outcomes. Study (1) provides an updated overview, critically assesses and identifies gaps in the current literature on the economic costs of T2D 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 **IV!** (**IV!**) approach; study (3) revisits and extends on these results via the use of panel data and **FE!** (**FE!**), 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 measurement error in self-reported diabetes. Study (4) investigates the effect of a diabetes diagnosis on employment as well as health behaviours in China, using longitudinal data and applying two distinct identification strategies: **FE!** and **MSM!** (**MSM!**) estimation.

The findings of the first paper document a considerable increase in studies on the economic costs of diabetes in **MIC!**s. It also illustrates that most of the evidence is based on cost-of-illness studies and the literature on adverse labour market effects of diabetes in **MIC!**s is scarce. The thesis fills part of this void and shows that self-reported diabetes has a considerable impact on employment probabilities of people living in Mexico and China. The findings are robust to the application of different estimation strategies. No consistent evidence of an adverse effect of diabetes on wages or working hours is found. The findings for Mexico indicate that it is the poor and less protected as well as women that are most negatively affected by the disease. Taking into account those unaware of the disease, the adverse effect of diabetes is reduced because undiagnosed diabetes itself does not show an adverse association with any labour market outcome. This suggests that the undiagnosed population is distinctly different from the diagnosed population, likely due to differences in health information and health status. With regards to the effect of a diabetes diagnosis on health behaviours, the results from China suggest that a diagnosis leads to moderate reductions in body mass index (BMI), waist circumference, alcohol and caloric consumption. Perhaps surprisingly, especially men appear to be able to lose weight and reduce their caloric consumption. Not accounting for unobserved heterogeneity leads to a change in the coefficient sign for the effect of a diagnosis on **BMI!** (**BMI!**)

and waist circumference, while the differences in estimates are less pronounced for other outcomes.

The thesis identifies a considerable economic burden of diabetes in **MIC!**s. Efforts to reduce this burden should consider inequities in the economic burden.

Contents

List of Figures

List of Tables

Abbreviations

BMI body mass index

FE fixed effects

IV instrumental variable

MSM marginal structural model

MIC middle-income country

Publications and statement of authorship

Publications arising from this thesis

Seuring2015a

This publication can be found at: `http://link.springer.com/article/10.1007%2Fs40273-015-0268-9`

Seuring2015

This publication can be found at: `http://www.sciencedirect.com/science/article/pii/S1570677X15000349`

Statement of jointly authored publications

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

Chapter ??:   Written by Till Seuring.

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

Seuring2015a

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.

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

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Till Seuring, Yevgeniy Goryakin and Marc Suhrcke designed the study. Till Seuring analysed the data. Till Seuring drafted the original manuscript which was critically reviewed by Yevgeniy Goryakin and Marc Suhrcke.

Chapter ??:   Till Seuring, Pieter Serneels and Marc Suhrcke designed the study. Till Seuring analysed the data. Till Seuring drafted the original manuscript which was critically reviewed by Pieter Serneels and Marc Suhrcke.

Chapter ??:   Till Seuring and Max Bachmann designed the study. Till Seuring analysed the data. Till Seuring drafted the original manuscript which was critically reviewed by Max Bachmann.

Chapter ??:   Written by Till Seuring.

1 General Introduction

2 The Economic Costs of Type 2 Diabetes: A Global Systematic Review

3 The Impact of Diabetes on Employment in Mexico

Pre-amble

The systematic review in Chapter **??** identified a paucity of studies on the labour market impact of diabetes in non-**HIC!**s (**HIC!**s). Further, even studies on **HIC!**s did not provide much information regarding the heterogeneity of effects accross 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. Chapters **??** and **??** therefore investigate the labour market impact of diabetes in a more comprehensive way than previous literature.

This study will use cross-sectional data from a large household survey in Mexico, assessing the impact of diabetes on employment probabilities. An **IV!** (**IV!**) strategy inspired by preceding studies from **HIC!**s 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 to be 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 **MIC!**s (**MIC!**s).

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 **IV!** (**IV!**) approach to address the issue of endogeneity, it takes advantage of the recently released third wave of the **MxFLS!** (**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 causal interpretation of the estimates, without having to rely on the untestable assumptions underlying the **IV!** approach.

Further, the study provides additional novel 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 **??** investigating in how far self-reported diabetes can be used to draw conclusions about the entire diabetes population, including those unaware of the condition using biomarker information. This area has hitherto received little research but is of great importance due to the large unaware diabetes population in **HIC!**s (**HIC!**s) and **LMIC!**s (**LMIC!**s). Using biomarker data it investigates in how far self-reported diabetes identifies the entire diabetes population and if findings based on self-reports can be extended to those unaware of the condition. This should help to better interpret estimates using self-reported diabetes as provided in Chapter **??**.

5 The effects of receiving a diabetes diagnosis on health behaviour and economic outcomes in China

Pre-amble

Chapters **??** and **??** provided evidence of the adverse impact of self-reported diabetes on employment probabilities in Mexico. However, if this is also the case in other **MIC!**s (**MIC!**s) is unclear. The study in Chapter **??** intents to provide further evidence using rich panel data covering a period of rapid economic transition in China. It further intents to provide information about the current success of the Chinese healthcare system in bringing about behaviour change in those diagnosed. 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.

This study again faces the problem of the potential endogeneity of diabetes. It uses an already established approach with the **FE!** (**FE!**) estimator. However, it adds a further identification strategy by making use of **MSM!**s (**MSM!**s), a strategy widely applied in epidemiology to account for time-variant confounding, in particular selection into treatment on pre-treatment outcome variables. It is less known in economics but nicely complements the **FE!** method. The aim of the study was to provide information on the success of current diabetes management in the Chinese healthcare system and to identify areas where improvements are needed to curb the burden of diabetes.

Abstract

A diabetes diagnosis entails important consequences for its recipients. They 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 behavioural risk-factors as well as on employment chances, two potentially intertwined factors. We used longitudinal data from the **CHNS!** (**CHNS!**), covering the years 1997 to 2011. Two complementary statistical techniques—marginal structural models and fixed effects panel estimation—were used to estimate the causal effect of a diabetes diagnosis on a series of behavioural risk-factors and employment probabilities. Both models suggest female employment chances to decline significantly as a result of a diabetes diagnosis (over 11 percentage points), but no adverse effects for men. Chinese men appear to respond to a diagnosis by significantly reducing their **BMI!** (**BMI!**), waist circumference and calorie consumption, in ways that are sustained over time. The effects on behavioural outcomes for women are smaller and less consistent. In light of the results it may be worthwhile for the Chinese healthcare system to focus efforts on addressing the needs of women with diabetes as it is them who have particular difficulties in improving their behavioural risk factors and who—perhaps as a consequence—pay the biggest price in terms of loss of employment chances. Future research is needed to unravel the mechanism behind these sex differences.

5.1 Introduction

Diabetes risk factors such as alcohol consumption, weight gain, smoking or caloric consumption are all related to the onset of diabetes as well as ensuing diabetes complications. They may further be influenced by the diabetes diagnosis itself as well as by a person's employment status. Research shows for instance that behaviour changes after a diabetes diagnosis can have positive health effects and reduce the risk of subsequent cardiovascular events(**Long2014**), may help in effectively managing blood glucose levels and achieving further treatment goals (**Zhou2016**). As a consequence, such changes may also affect the economic impact of diabetes if they cause a delay in or even prevent the onset of complications. Further, employment status may itself be related to diabetes risk factors, for example by affecting the time spend on physical activity or by increasing stress levels due to unemployment or due to challenges at the workplace, affect other risk behaviours such as smoking or alcohol consumption. In an effort to longitudinally investigate the impact of unemployment on health behaviours, **Colman2014** found heterogeneous effects of un-

employment, with it leading 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 (**Charles2008**), 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, employment and behavioural diabetes risk factors due to the danger of over-adjusting, as standard regression techniques such as **OLS!** (**OLS!**) or **FE!** are unable to account for multi-directional relationships. Similarly, there is a dearth of studies investigating longitudinally the impact of a diabetes diagnosis on behavioural diabetes risk factors, while taking into account the effect of employment status on both diabetes and diabetes risk factors. A further challenge faced by researchers investigating the effects of diabetes on both economic outcomes and risk factors are unobserved variables that may be biasing the estimates. In particular time-invariant ones such as poor early life conditions or time stable personal character trades, may simultaneously increase the probabilities to develop diabetes and to be unemployed or to engage in unhealthy behaviours.

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 and health behaviours. This is done via the use of **MSM!**s, an estimation strategy that is able to account for time-dependent confounding across time (**Robins2000**) when estimating the impact of a treatment, here a diabetes diagnosis, on the outcome of interest. This is the first time this strategy is used to estimate the impact of diabetes on employment status. We further complement this and test the robustness of **MSM!** to the potential violation of one of its crucial assumptions of no unmeasured confounding. Therefore, we estimate **FE!**s models that—while unable to account for the potentially simultaneous relationships—are able to take into account any unobserved time-invariant confounding additionally to confounding due to observed variables. Very different results to the **MSM!** would suggest considerable unobserved confounding. To assess further how important any unmeasured confounding may be, we additionally estimate **RE!** (**RE!**) models to compare the results from the **MSM!**s and **FE!** models against. Apart from these methodological contributions, the study also further extends the evidence base for the impact of diabetes on employment probabilities in **MIC!**s, where currently empirical information is only available for Mexico (**Seuring2016**). At the same time the study provides first, as far as we are aware, longitudinal evidence for the effect of a diabetes diagnosis on behavioural risk factors for diabetes complications in China or any **LMIC!** (**LMIC!**) for that matter.

More information about the effects of a diabetes diagnosis may be particularly important for **LMIC!**s such as China, where diabetes prevalence has surged from 1% in the early 1980s to about 10% in recent years (**Hu2011**; **Risk2016**). Confronting this diabetes epidemic puts a strain on healthcare systems (**Seuring2015a**), increasing the need to find highly cost-effective prevention and treatment options in very resource constraint settings (**WHOresearchpriorities2010**). 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.

So far, population-level longitudinal research on the effects of health information on post-diagnosis behaviour change is scarce and has been limited to **HIC!**s (**HIC!**s). The sole study on the effects of recently diagnosed diabetes on health behaviours found positive behaviour changes shortly after diagnosis in a USA population. However, the effects were mostly short lived and tended to dissipate over time, particularly considering weight loss (**Slade2012**). Slade created an "at risk" control group without diabetes that 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 averaged as well as **FE!** models for identification. While this allowed for the construction of a control group, the study was not able to account for the bidirectional relationship between diabetes and health behaviours.

Another study investigated the effect of a hypertension diagnosis on nutritional behaviours in China using a regression-discontinuity design and biomarker information on blood pressure (**Zhao2013a**). A crucial assumption in the study was that people above the hypertension threshold were indeed informed about that outcome 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. The results indicated that a diagnosis leads to reductions in fat consumption at the consecutive wave, though only for those economically better off. However, an important caveat of the study was that it was not always clear whether the participants received just the actual blood pressure measurement information and had to interpret these data themselves, or whether they were made explicitly aware of their hypertension (or also pre-hypertension) status (**Zhao2013a**). Further, the results may have limited generalisability, since the measured treatment effect is a very local one, applying only to the population around the hypertension threshold. The effects may have been different for people receiving their 'diagnosis' while already having very severe hypertension.

This study adds in several ways to the existing literature. First, it shows the impact of diabetes diagnosis on labour 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 simultaneously, 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 **MSM!** results, but also on the validity of some of its assumptions.

5.2 Methods

5.2.1 Study sample

The **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 (**Zhang2014d**). 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, including anthropometric measures of weight and height, reducing potential measurement issues. It further provides socioeconomic information, most importantly for this study about employment. The sample is limited to the adult population from age 18–64. The sample is not nationally representative and as such does not provide sampling weights (**Popkin2010**).

Overall, between 84% to 90% of the survey participants are followed up in the consecutive wave, with attrition being highest after 2006. Attrition in the **CHNS!** due to mortality is around 1% (**Popkin2010**). Other reasons mentioned by **Popkin2010** are loss in follow up due to migration, natural disasters and redevelopment of housing in the urban centres leading to relocations. We analysed if any of our variables of interest was significantly related to attrition and did only find lower calorie consumption to exhibit an association. Further, attrition was related to urbanization, level of education and being of younger age, suggesting that mostly younger, more urbanized participants tended to leave the survey.

5.2.2 Assessment of diabetes

We use self-reported information on a diabetes diagnosis to construct our diabetes indicator. We only rely on incident cases of self-reported diabetes, excluding individuals with self-reported diabetes at baseline. Given the chronic nature of diabetes, we assume that after the initial diagnosis diabetes persists for the rest of one's life. To construct a measure of diabetes duration for incidence cases we use 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, we used the midpoint between the last wave without diagnosis and the first wave with a diagnosis as the year of diagnosis.[1]

5.2.3 Assessment of outcomes

The economic outcome we focus on is employment status, based on a self-reported measure of if the person is currently working. People who are not working because they are students are excluded. We do include those that are not working due to any other reason such as doing housework, being disabled or being retired.

The behavioural outcomes we estimate are current smoking status, if alcohol was consumed equal to or more than three times per week, **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. Waist circumference is reported in centimetres. Finally, daily calorie consumption is 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. We also estimate models using overweight and obesity indicators instead of a continuous weight measurements. We do, however, not include them in our primary analysis as there is considerable discussion about the correct thresholds to use for Asian populations (**WHO2004**; **He2015**; **Zeng2014a**). We applied thresholds suggested by the China Obesity Task Force of a **BMI!** ≥ 24 to define overweight and a **BMI!** ≥ 28 to define obesity (**group2004body**). The results are presented in the appendix.

5.2.4 Statistical analysis

We use two statistical approaches to account for potential confounding: **MSM!**s (**MSM!**s) and **FE!** (**FE!**).

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[1]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 year of diabetes diagnosis self-reports.

Figure 5.1: **DAG!** for marginal structural model
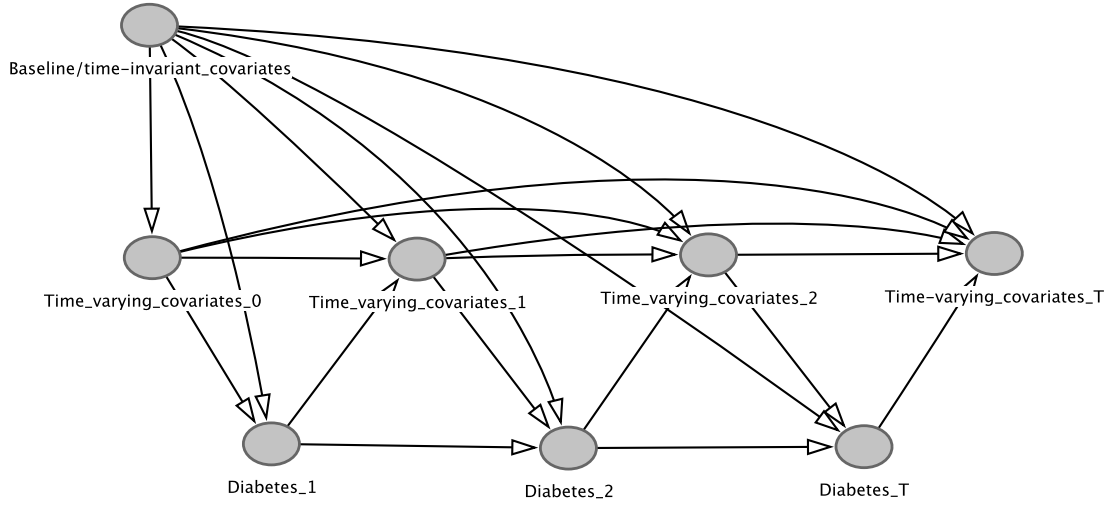
Notes **MSM!**s assume the absence of unobserved time-invariant and unobserved time-variant confounders but allow the past treatments to affect the current outcome (arrows going from Diabetes to time-variant covariates) and the past outcomes to affect the current treatment (arrows going from time-variant covariates to Diabetes). Lagged time-variant covariates, baseline and time-invariant covariates predict current diabetes status.

Marginal structural models

MSM!s apply inverse probability weights to adjust for confounding and selection bias as a result of time-varying confounders being affected by prior exposure to the treatment (**Robins2000**). Under the assumption of the **MSM!**(**Robins2000**)—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 Section **??** for a discussion of the validity of these assumptions in our case)—the causal **DAG!** (**DAG!**) shown in Figure **??** 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 such as increases weight or smoking. 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 could confound the relationship between a diabetes diagnosis and employment status. **MSM!** accounts for this by calculating weights based on the potential risk of a person being diagnosed at each time point.

To calculate these weights we first construct unstabilized weights using baseline values of time-variant confounders, time-invariant confounders as well as time-variant confounders lagged by one period to predict the probability of developing diabetes at each wave. We use lagged time-variant confounders because current diabetes status as reported in the survey was determined at some point within the current and the previous wave that were determined before the current diabetes status, to prevent reverse causality. The used predictors are 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 (**Zhang2014d**), to account for the impact of urbanization on diabetes risk (**Attard2012**). We also use secondary and university education, being married, having any medical insurance, being of Han ethnicity, living in a rural area, dummies for the different Chinese regions and the respective survey waves as predictors. Further we use inflation adjusted per-capita household income to adjust for effects of household wealth on diabetes. Finally, all outcome variables (employment status, alcohol consumption, smoking status, **BMI!**, waist circumference and average daily calorie consumption) are used as predictors.

Because unstabilized weights can be highly variable it is recommended to stabilize the weights (**Cole2008**). Using the unstabilized weights as the denominator, stabilized weights are calculated by dividing the denominator by the predicted treatment propensity from a model using only time-invariant confounders and baseline information of the time-variant confounders as predictors. Because our analysis is stratified by males and females, we create weights separately for both groups.

The **MSM!**s are estimated using **OLS!** for the continuous and a logistic model for the binary outcomes. For the logistic model we calculate average marginal effects for greater comparability with the results of the **FE!** models. All models are weighted by the stabilized weights constructed beforehand while adjusting for all baseline and time-invariant covariates used in the calculation of the stabilized weights, except for the respective outcome of interest. 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 likely are less efficient than truncated weights (**Cole2008**). The distribution of the inverse probability weights supports this decision as there are no extreme values and the mean weight is 1 (see Table **??**).

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 may be violated. 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. It does so by demeaning the confounding variables at each time point by 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 cannot not be estimated. Further, because the **FE!** model is not able to account for any treatment effects on other time-variant confounders, only a more limited set of confounders could be included compared to the **MSM!**. Otherwise our estimate of the effect of a diabetes diagnosis would likely be biased due to the inclusion of 'bad controls' (**Angrist2009a**). Bad controls are those 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 our outcome of interest, biasing the diabetes coefficient (**Angrist2009a**). The **FE!** models thus only includes controls for age, age squared, the level of urbanization, education, being married, having any medical insurance, living in a rural area, and dummies for the different Chinese regions and the respective survey waves. For the estimation of the effect of time since diagnosis, the linear age variable is dropped. In **FE!** models, two or more variables that change at the same rate between waves cannot be separately identified. Here this is the case with age and time-dummies, as both variables increase by one each additional year (**Wooldridge2012**). To identify the effect of diabetes duration 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.

Because it is not possible to retrieve marginal effects from a logistic **FE!** model, we use a **FE!** linear probability model instead. It generally produces very similar estimates

Figure 5.2: **DAG!** for fixed effects model
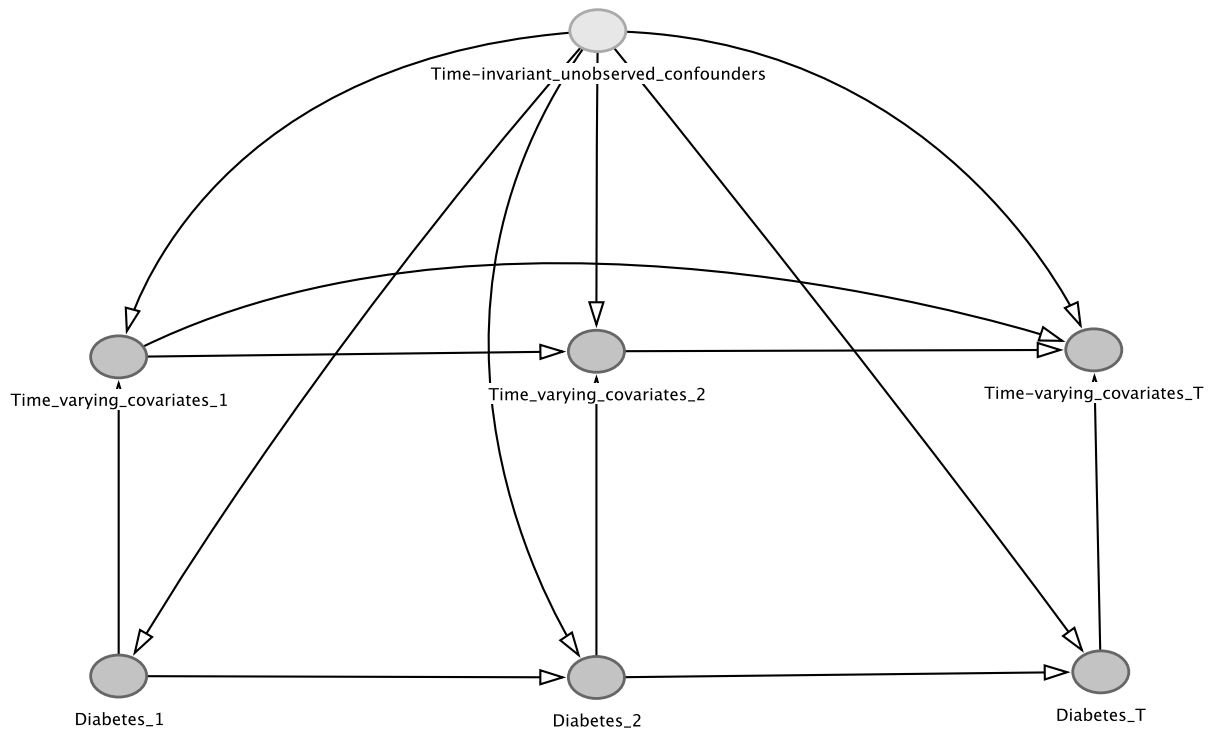
Notes **FE!** models account for time-invariant unobserved confounding (light grey circle), but still assume the absence of unobserved time-variant confounding. They further do not allow for past outcomes to affect the current treatment.

compared to non-linear models (**Angrist2009a**).

Multiple imputation

To deal with missing data, we used chained multiple imputation to impute the missing values in Stata 13 using the user written ICE command (**Royston2009**) and used the resulting data for all our estimated models. Overall, thirty imputed datasets were created. Imputation models included all variables used in the **MSM!**s. We imputed missing data in the same wave for which some data were recorded; we did not impute completely missing waves. Further, we did not impute missing diabetes information and instead 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 (**Klein2014**).

Numbers of observations

Because we used lagged variables to construct the stabilized weights for the **MSM!**s, the number of observations used in the **MSM!**s was lower than those used in the **FE!** models, where we did not use lagged variables. The summary statistics shown in Table **??** are based on the observations used in the **FE!** models.

Sensitivity analyses

We conduct three additional sensitivity analyses in order to test the robustness of our results to different assumptions and estimation strategies. First, we estimate all models using only covariate adjustment in a **RE!** model, to investigate in how far this 'naive' approach diverts from the "causal" estimates of the **FE!** and **MSM!**s. These results are presented and discussed together with the **MSM!** and **FE!** results. Second, we truncate weights at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile to investigate the sensitivity of the **MSM!**s 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 (**Cole2008**). Third, we estimate the **FE!** and **MSM!**s using the original non-imputed data to ascertain the extent to which multiple imputation affected the results.

5.3 Results

From the descriptive statistics, we can observe that people with diabetes in any wave are less likely to be employed. Looking at health behaviours, it is mainly men that smoke and report alcohol consumption while very few women do so. The prevalence of smoking and drinking was lower for men with diabetes; they also consumed fewer calories compared to men without diabetes. 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 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.

Table 5.1: 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	23413	284	23697	23577	336	23913

Predicting the denominator for the stabilized weights 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 may decrease the chances of being diagnosed with diabetes slightly, justifying the use of the **MSM!** in our employment models as well (Table **??**). 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. Interestingly, we do not find that higher household income levels are predictive of a diagnosis for men or women, despite what the descriptive statistics indicated. For women, higher age at baseline, increases in **BMI!** and waist circumference as well as living in a non-rural environment predict a diabetes diagnosis.

The results of our regression analysis are presented in Table **??**. Both the **FE!** model and the **MSM!** indicate that women with a diabetes diagnosis have reduced probabilities of being employed than their counterparts without diabetes, with a reduction of 11 percentage points in the **FE!** model and 12 percentage points in the **MSM!**. This translates into a relative reduction in employment probabilities between 16–17%. For men no such effect is observed.

There is a more ambiguous picture for the effect of a diabetes diagnosis on behavioural outcomes. There is no consistent—and only marginally significant evidence in the **MSM!**—that men reduced their smoking rate, however, a diabetes diagnosis led to a reduction in alcohol consumption as according to either model, though particularly so for the **MSM!**. For waist circumference, **BMI!** and calorie consumption, the **FE!** and **MSM!** both indicate reductions in **BMI!** of close to 0.7, of about 2 cm in waist circumference and of up to 170 calories per day for men. Results for women look different, in that 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 in the **FE!** model for **BMI!**, waist circumference and alcohol consumption.

The results of the **RE!** models appear to overestimate the impact of diabetes on female employment probabilities and to underestimate the impact of a diabetes diagnosis on reductions in **BMI!** and waist circumference. For the other outcomes, results are very similar to those from the **MSM!**s and **FE!** models.

Exploring the effect of a diabetes diagnosis over time, we first estimated a specification using time since diagnosis as a continuous variable. The results of the **FE!** model (Table **??**) indicate a steady reduction of female employment probabilities of almost two percentage points per year and of male alcohol consumption, **BMI!**, waist circumference and consumed calories. The **MSM!** again supports the finding of the **FE!** model, finding very

Table 5.2: Time variant and invariant predictors of a diabetes diagnosis (denominator of stabilized weights)

	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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results for province dummies omitted to preserve space. No observations for women with university education and diabetes.

Table 5.3: Analysis of the effect of a diabetes diagnosis on employment status and behavioural outcomes using fixed effects and marginal structural models

	(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 Standard errors in parentheses. Other control variables: age (only MSM), age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, per capite household income. Fixed/random effects: N=23443 (male sample), N=23702 (female sample); MSM: N=16047 (male sample), N=16658 (female sample).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

similar effects in terms of size and statistical significance. For women, the **MSM!** also support the finding of a reduction in employment probabilities, with the point estimate being somewhat larger compared to the **FE!** model. The evidence for changes in health behaviours is less consistent across models and outcomes, with the **FE!** indicating a reduction in waist circumference but not in **BMI!**, and the **MSM!** suggesting the opposite. The effect sizes for changes in health behaviours in women are about half the size to those found in men.

The results of the **RE!** models again likely overestimate the impact of diabetes on female employment probabilities and to underestimate the impact of a diabetes diagnosis on reductions in **BMI!** and waist circumference.

Table 5.4: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using fixed effects and marginal structural models

|	Odds ratios			Beta coefficients		
	(1) Employment	(2) Smoking	(3) Any alcohol	(4) **BMI!**	(5) Waist (cm)	(6) 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 Standard errors in parentheses. Other control variables: age (only MSM), age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. Fixed/random effects: N=23443 (male sample), N=23702 (female sample); MSM: N=16047 (male sample), N=16658 (female sample)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

In a second step we estimated a specification using year dummies to capture the potential non-linearity in the relationship between time since diagnosis and our outcomes. The results for both estimation methods are visualized in Figure **??** and presented in Tables **??** and **??** for the **FE!** and **MSM!**, respectively. Despite the smaller sample size in each group and hence lower precision, the **FE!** model still indicates a reduction in **BMI!** and waist circumference for men, especially in the first 8 to 10 years after diagnosis. A similar effect is found for females, especially for years 3 to 8 after diagnosis. 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. Using the **MSM!**, all point estimates suggest similar effects, but due to the lower sample size, we were not able to estimate the effects for females on smoking and alcohol consumption.

We conducted two sensitivity analyses. First, we truncated weights at the 1st and 99th percentile to investigate the sensitivity of the **MSM!**s to the most extreme weights. The estimated effects are very similar to those using the untruncated weights (Table **??** and **??**), suggesting no important loss in efficiency and supporting the decision to use untruncated weights. Second, we estimated the **FE!** and **MSM!**s using the original non-imputed data. The results are broadly similar (Tables **??**, **??**, **??** and **??**), in particular for the **FE!** model, still indicating a reduction in female employment chances 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.

Figure 5.3: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes (duration groups)

Marginal structural models

Fixed effects

Random effects
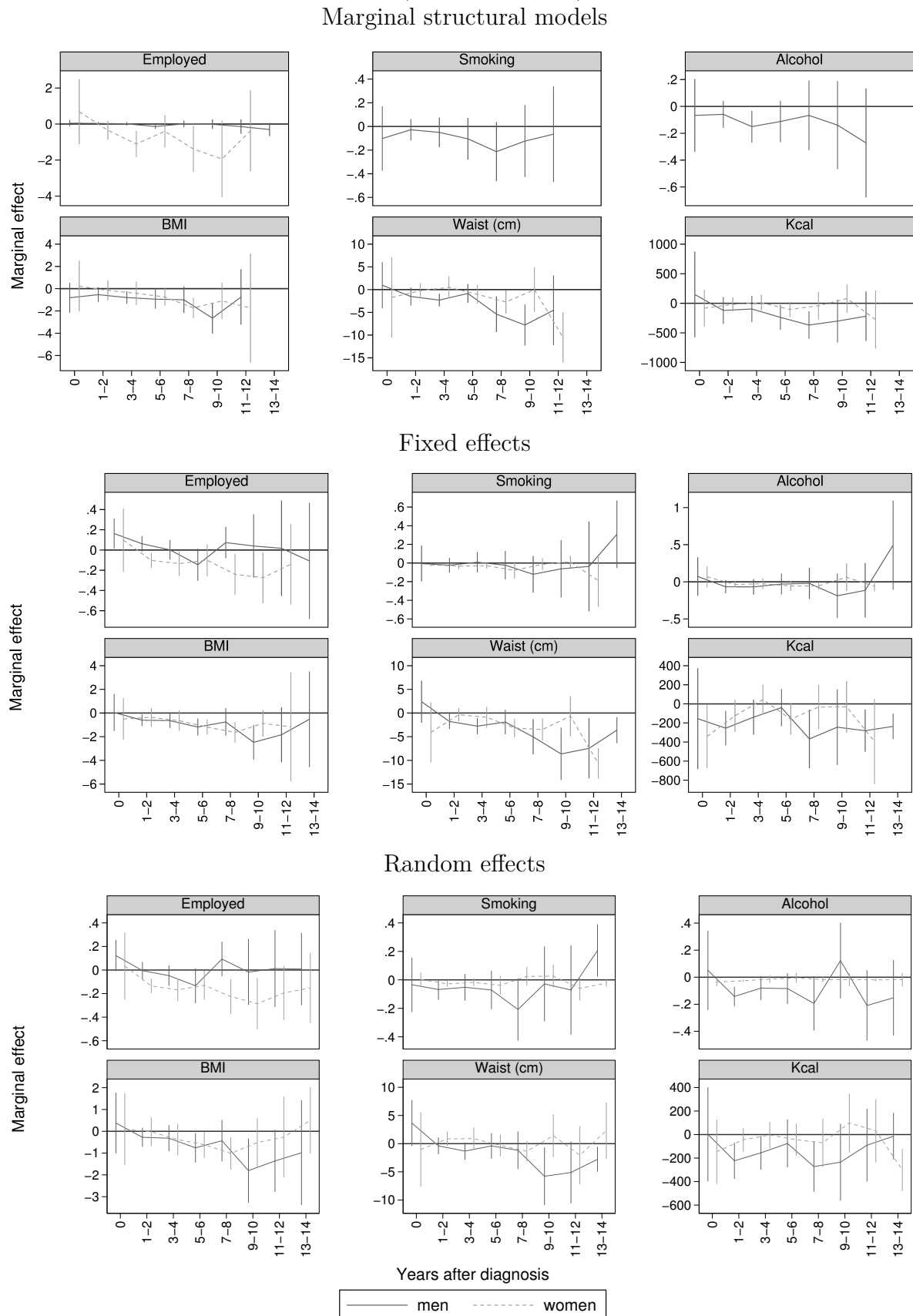
5.4 Disussion

Our results suggest that receiving a diabetes diagnosis in China led to a strong and lasting reduction in female, but not male employment probabilities. Looking at the behavioural risk factor outcomes, **BMI!** and waist circumference as well as risk behaviours such as alcohol and calorie consumption and potentially smoking were found to be reduced for men. For females, our primary results did not find as strong indications for changes in behavioural risk factors. Accordingly, it appears that women in China have to endure stronger adverse labour market effects and at the same time are less successful then men at making risk behaviour changes to reduce their risk of diabetes complications.

The **MSM!** models 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 high baseline **BMI!** and waist circumference levels help explain selection into a diabetes diagnosis, and thus need to be taken into account. Further, becoming employed appears to decrease the risk of being diagnosed with diabetes. The robustness checks using 'naive' regression in the form of **RE!** models further indicated that in this setting insufficiently accounting for confounding leads 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 after adjusting for observable covariates for risk behaviours (smoking and alcohol consumption) and caloric intake.

5.4.1 Limitations

While we used two estimation methods to reduce the influence of selection bias due to unobserved confounding, one limitation of the used approaches is their inability to account for all forms of selection simultaneously. 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. Exchangeability, or no unmeasured confounding, is not testable and could potentially be violated if not all time-invariant or time-variant confounders were accounted for. We tested for part of this assumption by estimating a **FE!** model, which suggested that unobserved time-invariant confounding may be of limited relevance. Consistency would have been violated if a diabetes diagnosis

had been reported but the person had actually not been diagnosed with diabetes. This is likely only violated in very rare cases of misreporting, given that specificity of diabetes self-report is very high in China (**Yuan2015**). 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 causing selection into a diabetes diagnosis based on changes in pre-treatment values of our outcomes of interest. Given that the **FE!** estimates were close to those of the **MSM!**s, it is likely that there was no strong confounding due to pre-treatment changes. Rather, the similarity of results suggests that it is important to account for some form of baseline values, be it via demeaning as in the **FE!** model or by using baseline values in the **MSM!**. Further, the **FE!** model is unable to account for the effect of confounders that are causally related with diabetes such as **BMI!** or waist circumference but may also have an effect on the outcome themselves. This may lead to an over- or underestimation of the effect of diabetes if the diabetes variable captures parts of the effect of very high **BMI!** levels (obesity). This may be the reason for some of the, albeit small, differences in point estimates between the **FE!** model and **MSM!**.

Finally, an important limitation is the that a diabetes diagnosis entails a variety of 'treatments' that are difficult to disentangle and may each have a distinct effect on the explored outcomes. Currently, we are only able to observe the combined effect of these treatments. Firstly, there is the provision of information at diagnosis, potentially causing increases in stress and anxiety, but may also providing an explanation for the experienced symptoms, both potentially affecting productivity. Secondly, a diagnosis also is the starting point for medical treatment, potentially alleviating symptoms and helping with weight loss, but also posing new challenges, in particular if treatment entails the exogenous provision of insulin or strict meal plans, potentially adding to the burden of diabetes in daily life. Thirdly, adherence 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 be able to prevent or delay debilitating complications. Fourthly, a diagnosis may also introduces lifestyle changes such as increasing exercise levels, eating healthier and reducing smoking or alcohol consumption, all potentially affecting the risk to develop further complications and to experience changes in productivity. In the current study, it is not possible to ascertain which of these factors and to what extend are affecting employment chances, but also the observed changes in weight loss. Only for the reductions in smoking and alcohol consumption, it seems reasonable to attribute them to diagnosis induced awareness to reduce these risk factors.

5.4.2 Potential mechanisms

The permanent reduction in male **BMI!** and waist circumference we have found has also been observed in a cohort of Danish patients (**DeFineOlivarius2015**), where weight increased the years preceding diagnosis, while after diagnosis weight decreased. The exact reasons for this decrease were unknown but attributed to motivation changes as a result of the diagnosis, concluding that time around the diagnosis may represent a window of opportunity to obtain long lasting weight change. Nonetheless, reductions in weight, as already eluded to in the limitations, may also be the result of treatment initiation with metformin or other diabetes drugs that have been shown to lead to weight reductions (**Yang2014**). Importantly, the reduction in **BMI!** in our study was accompanied by a reduction in waist circumference and energy intake. Given that in China diabetes incidence has been especially attributed to a high accumulation of visceral fat and central obesity (**Ma2014**), reductions in waist circumference therefore may have a particular positive effect on diabetes control and the prevention of comorbidities. This also allows for the interpretation that the changes in **BMI!** are due to reductions in fat and not lean body mass(**Klein2007**). The reduction in energy intake further suggest that the changes in weight are at least partly the result of changes in food consumption.

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 further diabetes complications that then reduced 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 (**Luo2015**) and may also affect the ability to successfully change behaviours. Lower income levels for females compared to men may also negatively affect the ability to receive adequate treatment following a diagnosis, limiting their ability to change health behaviours (**Luo2015**) and 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 are able to use fewer household revenues for their own healthcare. Further, 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 (**Peters2015**; **Peters2014a**;

Peters2014). Women are more likely to have spend more time in a pre-diabetes stadium (**Bertram2010**) and to cross the threshold only once the metabolic has significantly deteriorated, leading to a greater risk of cardiovascular disease and stroke (**Peters2015**). Supporting this, a study for China found a greater prevalence of diabetes comorbidities in Chinese women than men (**Liu2010**). In this light it may not be surprising that we find more conclusive evidence of worsening employment probabilities for women than for men. 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 then men, the long term effects of diabetes on their health are likely more severe than for men and consequently affect their employment status.

The found adverse effect of diabetes on employment is in line with other studies on the labour market impact of diabetes that find adverse effects of diabetes on women employment probabilities (**Minor2010**; **Latif2009**; **Harris2009**; **Seuring2016**)—often stronger than the effects experienced by men. Most comparable, due to the use of **FE!** with data for a similar time period, a study from Mexico also found significant reductions for both males and females of about 5 percentage points (**Seuring2016**). Taking into account the lower overall employment rate of Mexican women compared to men, this translated into an about 16% reduction in employment probabilities, a figure comparable to what Chinese women experienced. However, in Mexico also men experienced adverse effects, unlike to what we found for China.

The found effects on changes in behavioural risk factors can partly be compared to a study by (**Slade2012**) that used population level observational data to investigate the effect of a diabetes diagnosis on health behaviours in the USA. Our findings are similar in some respects, as both studies suggest a response to the diabetes diagnosis 'shock' by reductions in dietary choices—Slade also found a reduction in alcohol consumption—but not to a similar extend curb smoking. In terms of the effect on weight, both studies cannot be directly compared because Slade investigated the effect to be overweight or obese, while we used continuous weight measures due to the discussed difficulties of defining cut-off values for Asian populations. Nonetheless, the results from the overweight and obesity models we estimated do—similarly to Slade—not indicate important reductions in obesity after a diabetes diagnosis. However, while Slade finds a stronger initial reduction in weight status, he also finds that people with diabetes tended to return to be obese or overweight after some time. Our results suggested that man may manage to consistently reduce their probabilities to be obese, but not overweight, at least according to the **FE!** model. Importantly—and in concordance with our findings—he finds that simple covariate adjustment leads to estimates indicating an increase in overweight and obesity, underlining

the importance of accounting for unobserved heterogeneity.

5.5 Conclusion

Our results indicate changes in male health behaviours after a diabetes diagnosis in China. These findings are robust to the application of two distinct, but complementary econometric techniques. Further, women likely had to bear a larger diabetes burden also affecting their economic well-being, as evidenced by their reduction in employment probabilities. Potentially, one of the causes of these adverse economic effects is the lower ability of women to successfully change their behaviour as a result of the diagnosis. Further research should try to unravel the mechanisms behind these differential outcomes for men and women. 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 more emphasis on the adequate treatment options for women may be needed to reduce their burden of diabetes.

Stabilized weights

Table 5.5: Summary of stabilized weights

	Mean	Min	Max
Untruncated (men)	1.001343	.1740716	5.780513
Untruncated (women)	1.000773	.1661002	8.754402
Truncated 1 and 99 percentile (men)	.9997768	.8906016	1.107517
Truncated 1 and 99 percentile (women)	.9988097	.8323757	1.119154

5.5.1 Duration groups results

Table 5.6: 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	0.049	−.102	−.067	−.811	0.968	148.433
	(.087)	(.139)	(.138)	(.682)	(2.587)	(369.013)
1-2	0.034	−.028	−.059	−.535	−1.517	−121.424
	(.038)	(.046)	(.051)	(.340)	(.996)	(115.615)
3-4	0.012	−.050	−.150**	−.795***	−2.312***	−96.393
	(.042)	(.063)	(.060)	(.288)	(.712)	(113.071)
5-6	−.139**	−.105	−.112	−.937**	−.843	−237.957**
	(.068)	(.090)	(.078)	(.438)	(1.050)	(107.745)
7-8	0.010	−.213*	−.067	−.995*	−5.401***	−368.463***
	(.087)	(.127)	(.132)	(.602)	(1.991)	(117.513)
9-10	−.014	−.124	−.139	−2.648***	−7.791***	−300.917
	(.136)	(.155)	(.167)	(.699)	(2.294)	(184.269)
11-12	−.142	−.065	−.272	−.751	−4.542	−218.570
	(.203)	(.205)	(.206)	(1.262)	(3.896)	(212.524)
13-14	−.304					
	(.186)					
Female sample						
0	0.110			0.233	−1.713	−82.792
	(.132)			(1.158)	(4.483)	(158.560)
1-2	−.063			−.153	−.238	−17.870
	(.049)			(.450)	(.850)	(59.249)
3-4	−.210***			−.409	0.506	11.054
	(.071)			(.537)	(1.229)	(67.419)
5-6	−.074			−.743*	−1.038	−104.696
	(.087)			(.396)	(1.063)	(64.981)
7-8	−.262**			−1.721***	−2.724**	−41.099
	(.122)			(.464)	(1.315)	(119.484)
9-10	−.355**			−1.095	−.012	80.030
	(.172)			(.827)	(2.495)	(122.037)
11-12	−.072			−1.739	−10.515***	−275.508
	(.213)			(2.489)	(2.806)	(250.141)

Notes Other control variables: age, age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=13195 (male sample), N=14549 (female sample).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Table 5.7: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using fixed effects (duration groups)

	Odds ratios			Beta coefficients		
	(1) Employment	(2) Smoking	(3) Any alcohol	(4) **BMI!**	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.163**	−.006	0.072	0.049	2.397	−155.323
	(.075)	(.098)	(.132)	(.792)	(2.258)	(268.552)
1-2	0.062	−.023	−.067	−.605**	−1.782**	−254.427***
	(.039)	(.040)	(.045)	(.252)	(.825)	(92.421)
3-4	0.002	0.008	−.068	−.639**	−2.768***	−139.397
	(.050)	(.055)	(.052)	(.314)	(.870)	(93.516)
5-6	−.145*	−.023	−.030	−1.183***	−1.901	−39.053
	(.081)	(.077)	(.071)	(.362)	(1.304)	(98.730)
7-8	0.074	−.121	−.021	−.751	−5.037***	−367.421**
	(.079)	(.100)	(.106)	(.588)	(1.896)	(156.656)
9-10	0.040	−.062	−.188	−2.472***	−8.642***	−244.372
	(.159)	(.157)	(.152)	(.741)	(2.812)	(201.960)
11-12	0.017	−.037	−.114	−1.835	−7.465**	−281.008**
	(.240)	(.245)	(.187)	(1.181)	(3.238)	(112.461)
13-14	−.108	0.308*	0.494	−.524	−3.615***	−235.985***
	(.293)	(.184)	(.306)	(2.059)	(1.383)	(67.961)
Female sample						
0	0.098	−.019**	0.067	−.505	−4.090	−340.952**
	(.159)	(.008)	(.072)	(.896)	(3.235)	(169.411)
1-2	−.103***	−.034**	−.036*	−.364	−.355	−124.847
	(.037)	(.015)	(.020)	(.404)	(.717)	(85.402)
3-4	−.134**	−.028*	−.025	−.648	−.896	45.970
	(.062)	(.016)	(.036)	(.435)	(1.120)	(79.063)
5-6	−.100	−.079*	−.056*	−1.184***	−3.176***	−160.445*
	(.080)	(.045)	(.033)	(.323)	(.990)	(83.164)
7-8	−.240**	−.013	−.054**	−1.637***	−3.482***	−32.865
	(.103)	(.032)	(.026)	(.433)	(1.182)	(117.750)
9-10	−.274**	0.012	0.062	−.876	−.639	−30.676
	(.128)	(.031)	(.094)	(.568)	(2.147)	(137.658)
11-12	−.140	−.189	−.059	−1.163	−10.633***	−393.884*
	(.202)	(.143)	(.036)	(2.344)	(1.618)	(227.502)

Notes Other control variables: age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=13195 (male sample), N=14549 (female sample).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Robustness checks

MSM!s using truncated weights

Table 5.8: 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 Standard errors in parentheses. Other control variables: age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=16047 (male sample), N=16658 (female sample).

Table 5.9: Effect of time since diabetes diagnosis on employment status and behavioural outcomes using MSM with truncated stabilized weights (1st and 99th pct; imputed)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Male sample						
0	0.075	−.102	−.067	−.345	2.302	−86.368
	(.077)	(.139)	(.138)	(.839)	(2.872)	(247.229)
1-2	0.012	−.028	−.059	−.375	−.812	−224.716**
	(.036)	(.046)	(.051)	(.297)	(.957)	(95.028)
3-4	−.018	−.050	−.150**	−.723**	−1.965***	−167.769*
	(.042)	(.063)	(.060)	(.305)	(.735)	(86.996)
5-6	−.139**	−.105	−.112	−1.034***	−.891	−203.814**
	(.066)	(.090)	(.078)	(.392)	(1.096)	(102.051)
7-8	0.018	−.213*	−.067	−.944*	−4.935***	−347.441***
	(.084)	(.127)	(.132)	(.563)	(1.846)	(125.660)
9-10	−.033	−.124	−.139	−2.627***	−6.998***	−232.656
	(.122)	(.155)	(.167)	(.689)	(2.453)	(177.019)
11-12	−.151	−.065	−.272	−.889	−4.363	−212.318
	(.202)	(.205)	(.206)	(1.123)	(3.500)	(189.967)
13-14	−.305*					
	(.185)					
Female sample						
0	0.112			0.685	−.060	−104.652
	(.128)			(1.289)	(4.993)	(158.546)
1-2	−.104**			0.205	0.698	−18.334
	(.047)			(.452)	(.834)	(64.456)
3-4	−.208***			−.299	0.889	6.982
	(.068)			(.520)	(1.191)	(65.213)
5-6	−.138*			−.569	−.793	−122.064*
	(.082)			(.364)	(1.087)	(64.349)
7-8	−.249**			−1.662***	−2.125	−5.039
	(.121)			(.502)	(1.315)	(120.139)
9-10	−.373**			−1.019	0.409	72.475
	(.169)			(.829)	(2.523)	(132.027)
11-12	−.087			−1.858	−10.814***	−251.975
	(.214)			(2.510)	(2.749)	(234.610)

Notes Standard errors in parentheses. Other control variables: age squared, region, urban, education, Han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=13195 (male sample), N=14549 (female sample).

46

Results using non-imputed data

Table 5.10: Analysis of the effect of a diabetes diagnosis on employment status and be-havioural outcomes using fixed effects and marginal structural models (no imputation)

	(1) Employment	(2) Smoking	(3) Any alcohol	(4) BMI	(5) Waist (cm)	(6) Calories (kcal)
Marginal structural model						
Male sample						
Diabetes	0.050	−.042	−.112**	−.641***	−1.224	−152.149
	(.046)	(.041)	(.049)	(.220)	(.803)	(123.921)
Female sample						
Diabetes	−.081*	−.028*	−.075	−.583	−.935	−50.350
	(.049)	(.015)	(.045)	(.393)	(.866)	(56.914)
Fixed effects						
Male sample						
Diabetes	0.028	−.000	−.063*	−.868***	−2.448***	−152.027**
	(.030)	(.033)	(.034)	(.170)	(.517)	(68.421)
Female sample						
Diabetes	−.107***	−.024**	−.022	−.638**	−1.049*	−81.554*
	(.034)	(.012)	(.019)	(.288)	(.636)	(48.970)

Notes Standard errors in parentheses. Other control variables: age (only MSM), age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. FE: N=21444 (male sample), N=23128 (female sample), MSM: N=10039 (male sample), N=11489 (female sample).

Table 5.11: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using fixed effects and marginal structural models (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	0.027	−.020	−.024	−.221**	−.705**	−80.594**
	(.018)	(.016)	(.017)	(.087)	(.295)	(39.681)
Female sample						
Time since diagnosis	−.030	−.009	−.039	−.413*	−.598	−14.552
	(.022)	(.006)	(.025)	(.216)	(.376)	(24.269)
			Fixed effects			
Male sample						
Time since diagnosis	−.003	0.005	−.003	−.164***	−.581***	−22.700
	(.008)	(.007)	(.007)	(.044)	(.121)	(12.487)
Female sample						
Time since diagnosis	−.026**	−.006*	−.005	−.163**	−.325*	−16.888
	(.009)	(.002)	(.004)	(.060)	(.148)	(10.337)

Notes Standard errors in parentheses. Other control variables: age (only MSM) age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. FE: N=22066 (male sample), N=23051 (female sample), MSM: N=10028 (male sample), N=11465 (female sample).

Table 5.12: 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	0.107	0.051	−.149	−1.004*	1.113	314.866
	(.080)	(.150)	(.175)	(.562)	(1.103)	(409.370)
1-2	0.038	−.050	−.050	−.609**	−1.727*	−146.884
	(.047)	(.052)	(.057)	(.284)	(.973)	(148.251)
3-4	0.000	−.038	−.095	−1.028**	−3.164	−695.698***
	(.)	(.159)	(.117)	(.460)	(2.066)	(190.065)
Female sample						
0	0.134	0.000	0.000	−.102	−1.362	−111.379
	(.179)	(.)	(.)	(1.544)	(6.099)	(207.839)
1-2	−.079	−.019**	−.052*	−.484	−.581	−32.105
	(.069)	(.008)	(.029)	(.487)	(1.006)	(67.670)
3-4	0.000	0.000	0.000	−5.590*	−8.485***	1.258
	(.)	(.)	(.)	(3.286)	(1.792)	(258.264)

Notes Due to Standard errors in parentheses. Other control variables: Age, age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=10028 (male sample), N=11465 (female sample).

Table 5.13: 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	0.132	−.014	0.125	−.009	1.439	−268.692
	(.072)	(.085)	(.136)	(.702)	(1.879)	(215.527)
1-2	0.065	−.013	−.053	−.849***	−2.391***	−244.075**
	(.039)	(.041)	(.045)	(.212)	(.663)	(91.888)
3-4	0.009	0.058	−.035	−.720*	−2.642**	−105.039
	(.048)	(.054)	(.053)	(.334)	(.824)	(100.459)
5-6	−.127	0.029	−.006	−1.168***	−1.733	−14.828
	(.080)	(.079)	(.078)	(.351)	(1.204)	(104.926)
7-8	0.118	−.089	0.030	−.617	−4.227*	−319.563
	(.081)	(.090)	(.087)	(.537)	(1.871)	(166.278)
9-10	0.018	0.030	−.115	−2.199***	−9.351***	−189.090
	(.154)	(.132)	(.145)	(.659)	(2.503)	(224.518)
11-12	−.032	0.097	0.058	−2.060	−9.185**	−162.422
	(.250)	(.200)	(.097)	(1.074)	(2.868)	(94.541)
13-14	−.116	0.341*	0.599	−.527	−3.481***	−146.776*
	(.312)	(.153)	(.311)	(1.959)	(.864)	(68.253)
Female sample						
0	0.117	−.019*	0.066	−.811	−4.079	−372.137*
	(.154)	(.008)	(.072)	(.912)	(3.403)	(171.871)
1-2	−.091*	−.032*	−.037	−.324	−.383	−133.764*
	(.037)	(.014)	(.021)	(.417)	(.681)	(61.475)
3-4	−.144*	−.024	−.025	−.857	−1.051	26.559
	(.061)	(.014)	(.039)	(.458)	(1.184)	(85.752)
5-6	−.118	−.080	−.062*	−1.243***	−2.531**	−190.484*
	(.080)	(.046)	(.031)	(.348)	(.958)	(94.117)
7-8	−.255*	0.004	−.050	−1.823***	−3.976**	−47.473
	(.102)	(.020)	(.026)	(.454)	(1.217)	(133.625)
9-10	−.249*	0.016	0.064	−1.121	−.803	−89.938
	(.125)	(.033)	(.102)	(.653)	(2.277)	(136.611)
11-12	−.197	−.224	−.069	−.878	−10.898***	−563.138*
	(.170)	(.172)	(.041)	(2.888)	(1.724)	(240.085)

Notes Standard errors in parentheses. Other control variables: age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. N=22066 (male sample), N=23051 (female sample).

Overweight and obesity results

Table 5.14: Analysis of the effect of a diabetes diagnosis on overweight and obesity

|	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 Standard errors in parentheses. Other control variables: Age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. FE/RE: N=23443 (male sample), N=23702 (female sample). MSM: N=16047 (male sample), N=16658 (female sample).

Table 5.15: Analysis of the effect of time since diagnosis on overweight and obesity

	Males		Females	
	(1)	(2)	(3)	(4)
	Overweight	Obese	Overweight	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 Standard errors in parentheses. Other control variables: Age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. FE/RE: N=23443 (male sample), N=23702 (female sample). MSM: N=16047 (male sample), N=16658 (female sample).

Figure 5.4: Analysis of the effect of time since diabetes diagnosis on overweight and obesity (duration groups)

Marginal structural models

Fixed effects

Random effects
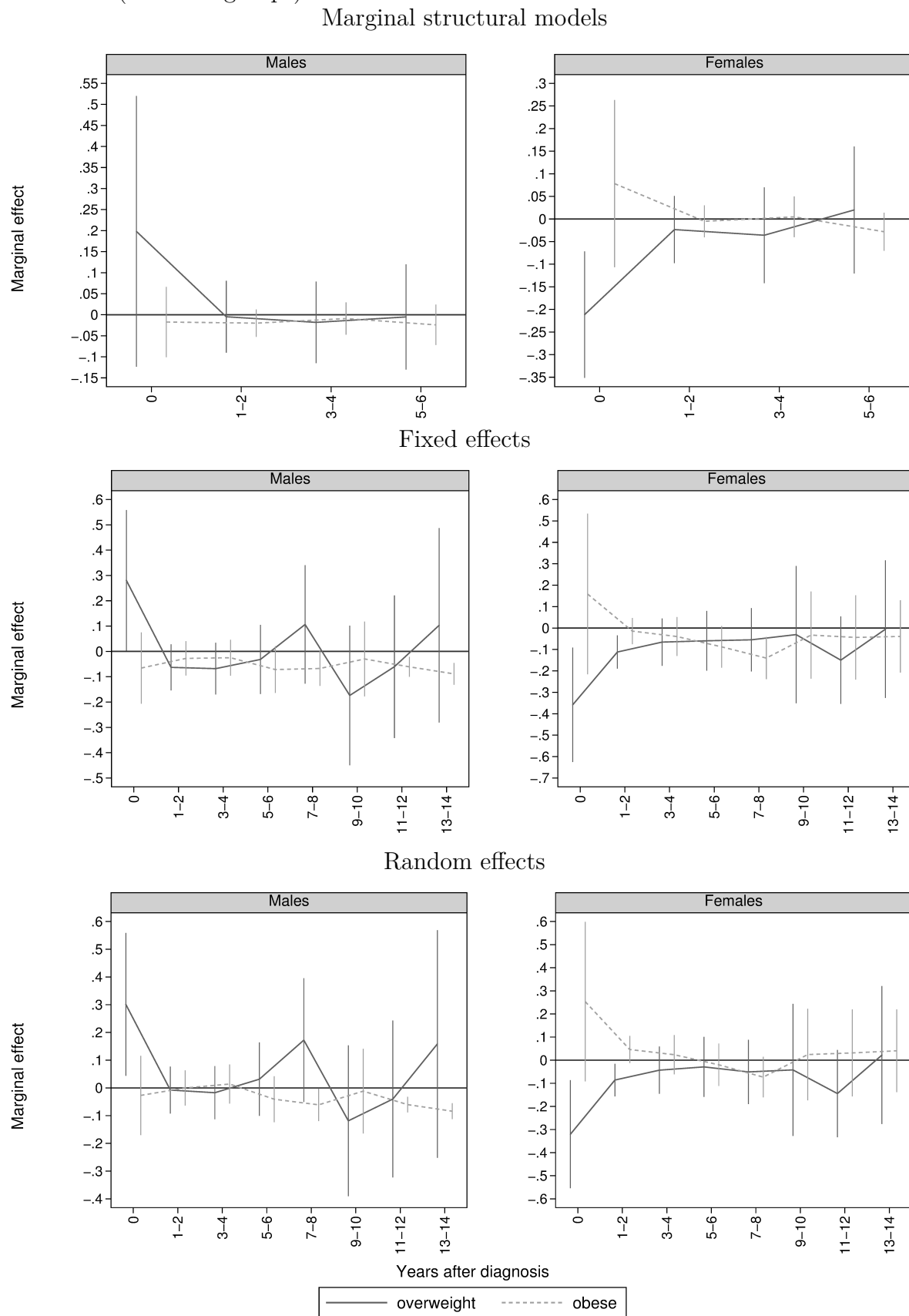
Notes: For MSM, effects after 6 years could not be estimated due to too few observations.

6 Discussion and conclusions

Appendix