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 on employment status and behavioural risk-factors, two potentially intertwined factors. We use longitudinal data from the China Health and Nutrition Survey (CHNS), covering the years 1997 to 2011. Two complementary statistical techniques—marginal structural models and fixed effects panel estimation—are used for the main statistical analysis. Both strategies find distinct patterns for males and females. The suggest a decrease in female employment chances 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. Chinese men, however, do not see their employment probabilities to be 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 in women to narrow these inequities.

0.1 Introduction

Behavioural 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. 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. An important economic outcome that has received relatively little attention in middle-income countries (MICs) is employment status, especially with diabetes appearing increasingly earlier in a person's productive lifespan with increasing obesity rates at earlier stages of life. It has been shown that diabetes can affect labour market outcomes in high-income countries (HICs), but also in MICs (Seuring, Serneels, et al., 2016). It seems that a diabetes diagnosis may present an important opportunity to start reducing risk factors for diabetes complications (De Fine Olivarius et al., 2015) and hence also reduce the economic burden of diabetes to the individual. It would therefore be important to determine in how far being diagnosed with diabetes is currently related to employment probabilities and changes in behavioural risk factors and in how far the latter might be affecting the former.

However, one of the challenges of determining a causal relationship between diabetes, employment status and changes in behavioural risk factors is their potential interrelatedness. For example, employment status might by affecting weight status by reducing the time spend on physical activity due to reductions in available leisure time, or may promote risk factors such as smoking behaviour or energy intake that can both affect the probability to develop diabetes as well as to develop diabetes related complications, by increasing stress levels. In an effort to longitudinally investigate the impact of unemployment on health behaviours, Colman and Dave (2014) found heterogeneous effects of unemployment, 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 (Charles and Decicca, 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 with behavioural diabetes risk factors. Using regression techniques such as ordinary least squares (OLS) or fixed effects (FE) it is 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. Similarly, there is a dearth of studies investigating 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, again potentially biasing the estimates. Apart from time-varying confounding due to observed covariates, a further challenge faced by researchers investigating the effects of diabetes are unobserved variables. In particular time-invariant confounders, 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 marginal structural models (MSMs), an estimation strategy that 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 the first time this strategy is used to estimate the impact of diabetes on an individual's employment status or behavioural risk factors for diabetes complications. We further complement this strategy and test the robustness of the MSM to the potential violation of one of its crucial assumptions, no unmeasured confounding. To do this, we estimate FE models that—while unable to account for the potentially simultaneous relationships—are able to adjust for any unobserved time-invariant confounding additionally to confounding due to observed variables. Very different results to the MSM may then suggest a violation the assumption of no unobserved confounding. To further investigate the extent of confounding, we additionally estimate random effects (RE) models to compare the results from the MSMs and FE models against. Apart from these methodological contributions, the study further extends the evidence base for the impact of diabetes on employment probabilities in MICs, where currently empirical information is only available for Mexico (Seuring, Serneels, et al., 2016). 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 low- and middle-income country (LMIC) for that matter.

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, Archangelidi, et al., 2015), increasing the need to find highly cost-effective prevention and treatment options in very resource constraint settings (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., 2005; Latif, 2009; Seuring, Goryakin, et al., 2015) and individual FE models (Seuring, Serneels, et al., 2016). However, while an IV approach could potentially account for all forms of confounding, the validity of the used instruments is at least questionable (Seuring, Serneels, et al., 2016). 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 in the USA, finding positive behaviour changes shortly after diagnosis. However, 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 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 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, it may not have been able to sufficiently account for the potential predetermination of the diabetes diagnosis by earlier values of the dependent variable. 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. (2013) 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 the 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. (2013) it was not always clear to what extend participants where 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 was a very local one, applying only 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 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 the MSM results, but also on the validity of some of its assumptions.

0.2 Methods

0.2.1 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 (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, 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 (Popkin et al., 2010).

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% (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 analysed if any of our variables of interest was significantly related to attrition at any wave and did only find lower calorie consumption and being unemployed to exhibit an association. Having diabetes was not related to 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. Attrition rates between the waves are shown in Table 0.5.

0.2.2 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. To construct a measure of diabetes duration for incidence 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, we used the midpoint between the last wave without diagnosis and the first wave with a diagnosis as the year of diagnosis.[1]

0.2.3 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 reported to not be working due to being students were excluded. We did include those that are not working due to any other reason such as doing housework, being disabled or being retired.

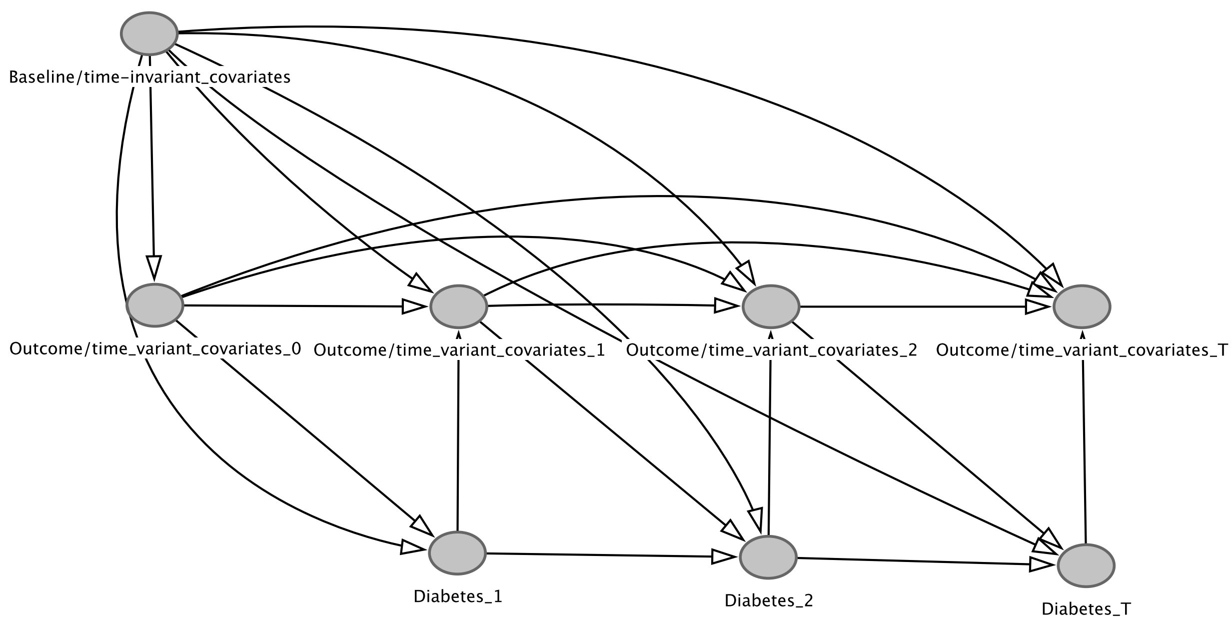
The behavioural outcomes we estimate are current smoking status, if alcohol was consumed equal to or more than three times per week, body mass index (BMI), waist circumference in centimetres and daily calorie consumption. Smoking status and alcohol consumption are self-reported, while BMI and waist circumference are based on anthropometric measurements, minimizing potential reporting errors. 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 measurement. We do, however, not include them in our primary analysis as there is considerable discussion about the correct thresholds to use for Asian populations to define overweight and obesity (He et al., 2015; WHO, 2004; Zeng et al., 2014). 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).

0.2.4 Statistical analysis

We use two statistical approaches to account for potential confounding: marginal structural models (MSMs) and fixed effects (FE).

[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 self-reports of the year of diagnosis.

Figure 0.1: DAG for 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) 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

MSMs 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 (Robins et al., 2000). Under the assumption 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 Section 0.4 for a discussion of the validity of these assumptions in our case)—the causal direct acyclic graph (DAG) shown in Figure 0.1 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 (Zhang et al., 2014), to account for the impact of urbanization on diabetes risk (Attard et al., 2012). 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 (Cole and Hernan, 2008). 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.

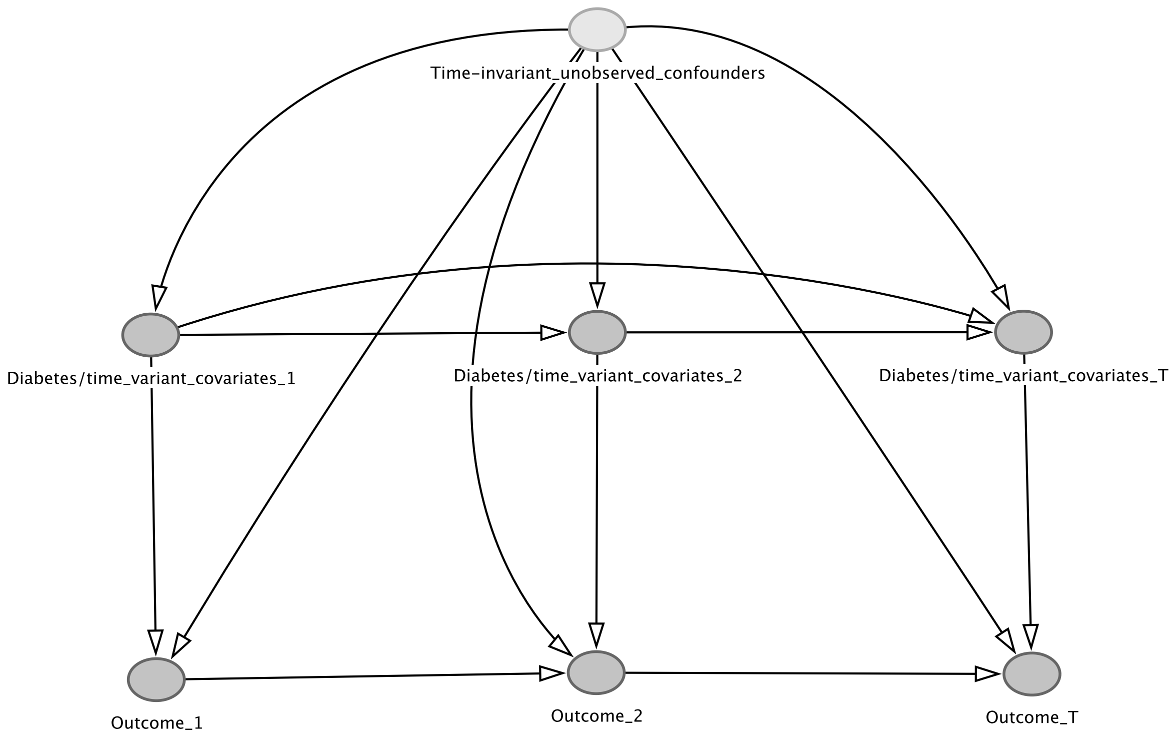
The MSMs are estimated using OLS for the continuous and a logistic model for the binary outcomes. For the logistic model we calculate average marginal effects for greater comparability with the results of the FE models. All models are weighted by the stabilized weights constructed beforehand while adjusting 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 (Cole and Hernan, 2008). The distribution of the inverse probability weights supports this decision as there are no extreme values and the mean weight is 1 (see Table 0.6).

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 as shown in the DAG in Figure 0.2. 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 cannot not 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' (Angrist and Pischke, 2008). Bad controls 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 and Pischke, 2008). Our FE specifications thus only include controls for age, 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. 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 (Wooldridge, 2012). 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

Figure 0.2: 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, i.e. diabetes status.

increase at the same rate as time.

Because it is not possible to retrieve average marginal effects from a logistic FE model, we use a linear FE model instead. It generally produces very similar estimates compared to non-linear models (Angrist and Pischke, 2008).

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 (Royston and White, 2009). Overall, thirty imputed datasets were created. 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 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 (Klein, 2014).

Numbers of observations

Because we used lagged 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 models, where we do not use lagged variables. The summary statistics shown in Table 0.1 are based on the observations used in the FE models. The number of observations is stated below each table.

Sensitivity analyses

We conduct four 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 MSMs. These results are presented and discussed together with those of the MSM and the FE model. Second, we truncate weights at the 1st and 99th 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 and Hernan, 2008). Third, we estimate the FE and MSMs using the original non-imputed data to ascertain the extent to which multiple imputation affected the results. Fourth, we estimate the 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.

0.3 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 is lower for men with diabetes; they also consume 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.

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 decreases the chances of being diagnosed with diabetes slightly, justifying the use of the MSM in our employment models as well (Table 0.2). 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 and waist circumference at baseline, increases in BMI as well as living in a non-rural environment predict a diabetes diagnosis.

Table 0.1: 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	23159	284		23369	333	

The results of our regression analysis are presented in Table 0.3. Both theMSM and FE model indicate that women with a diabetes diagnosis have lower probabilities of being employed than their counterparts without diabetes, with a reduction of 12 percentage points in the MSM and 11 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 smoking cessation and alcohol consumptions, who 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.

The results of the RE models suggest 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.

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 0.4) 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 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

Table 0.2: Time variant and invariant predictors of a diabetes diagnosis (denominator of stabilized weights)

	Males		Females	
	(1)	(2)	(3)	(4)
	β	SE	β	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 0.3: 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 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).

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

Table 0.4: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes using MSM, FE and RE

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

results for the different estimation methods are visualized in Figures 0.3, 0.4 and 0.5 and presented in Tables 0.7, 0.8 and 0.9 for the MSM, FE and RE model, respectively. Despite the reduced sample size in each group and hence lower precision, the MSM model still indicates a reduction in female employment chances and male BMI, waist circumference and calorie consumption as well as smoking and alcohol consumption, especially in the first 8 to 10 years after diagnosis. 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 and alcohol consumption due to the low prevalence of these risk factors in females, the lower sample size in the MSM and the reductions in sample size in each duration group. Using the FE model, all point estimates suggest 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 (Table 0.10 and 0.11), suggesting no important loss in efficiency and supporting the decision to use untruncated weights. The results using non-imputed data are broadly similar (Tables 0.12, 0.13, 0.14, 0.15 and 0.16), 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. 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 0.17 and 0.18 and Figure 0.6. Nonetheless, the point estimates still show a reduction in obesity, in particular over time and for men, supporting the reductions found using continuous measurements. The coefficients for overweight are difficult to interpret as it is unclear if the negative coefficient is caused by people transferring into the obesity or into normal weight.

Figure 0.3: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes (duration groups, marginal structural model)

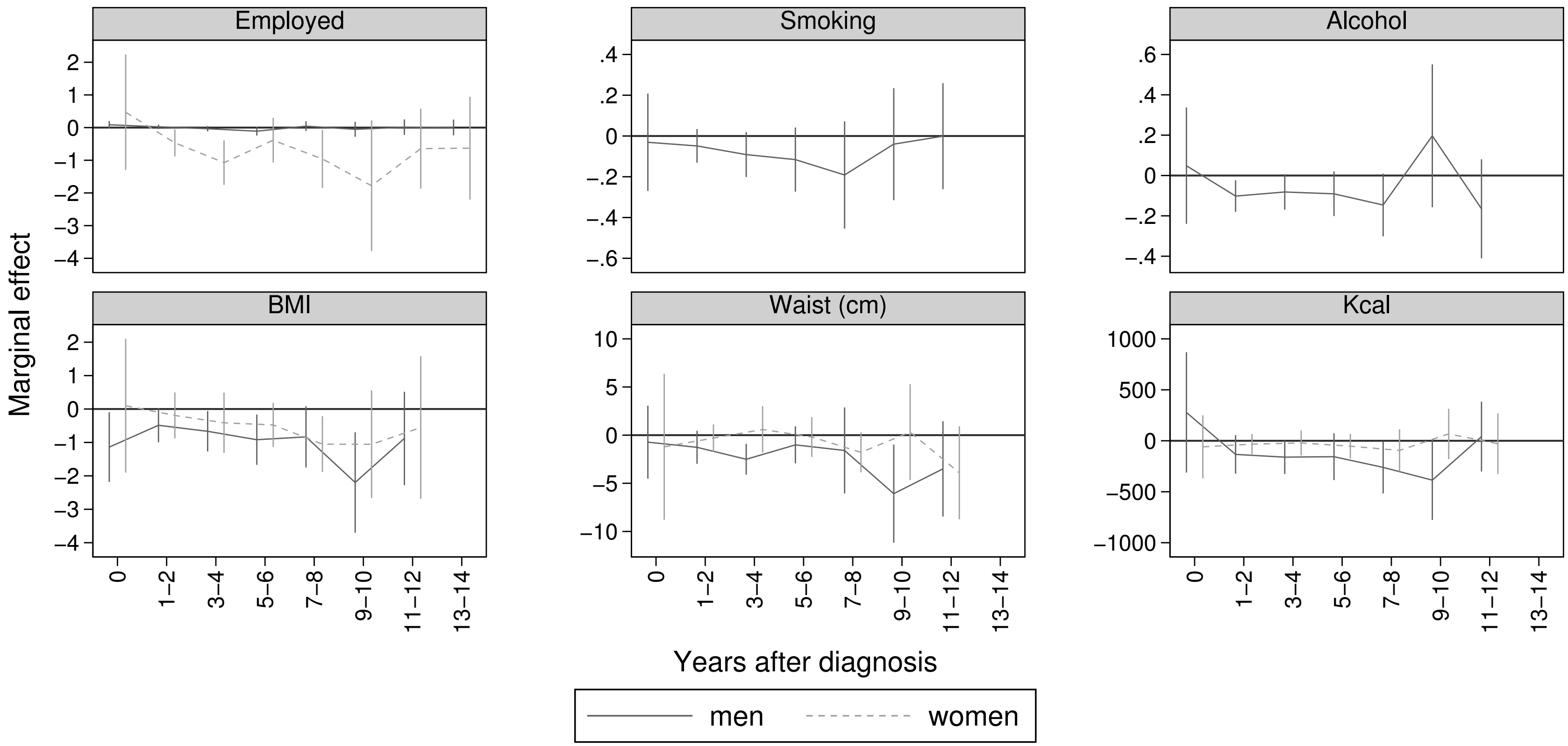


Figure 0.4: Analysis of the effect of time since diabetes diagnosis on employment status and behavioural outcomes (duration groups, fixed effects)

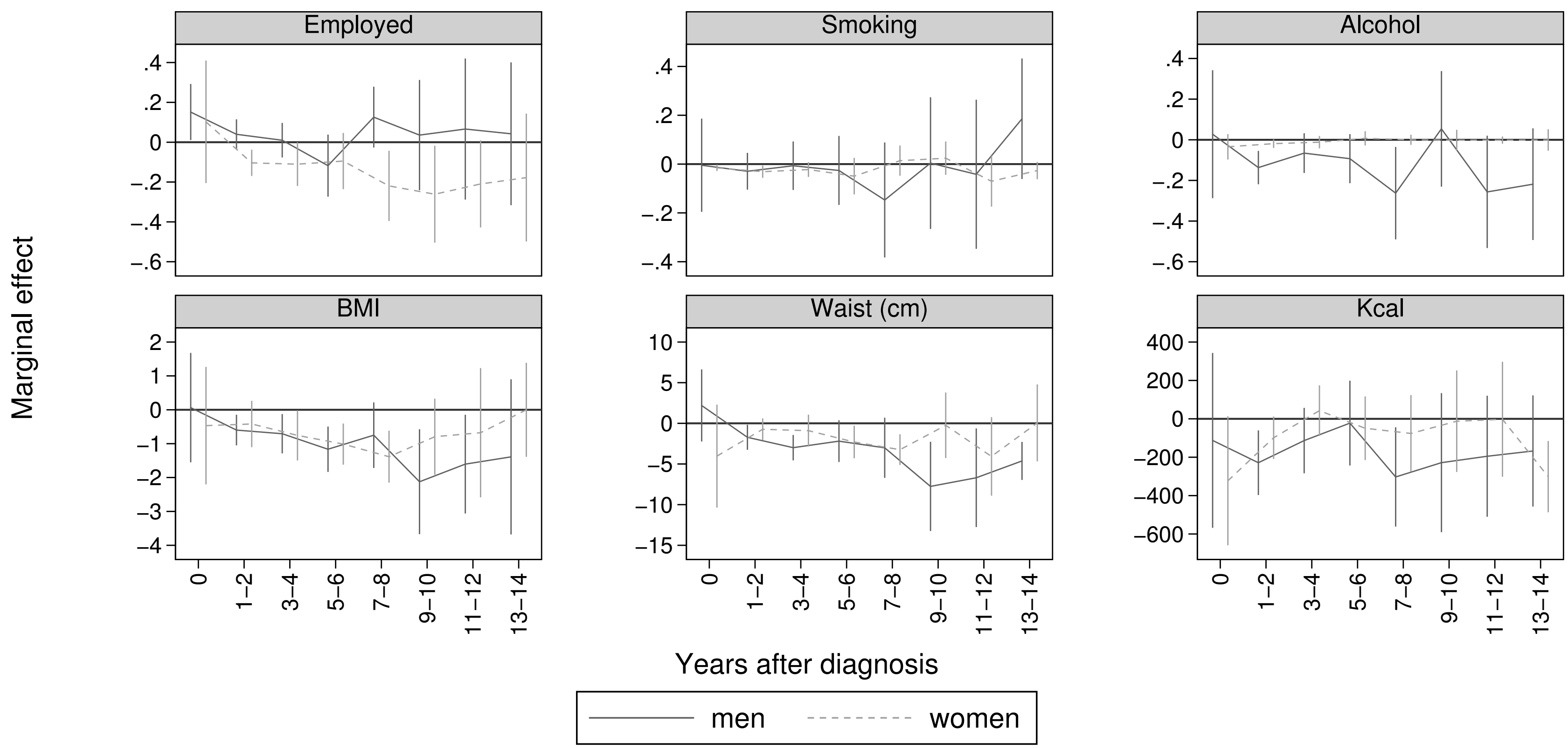
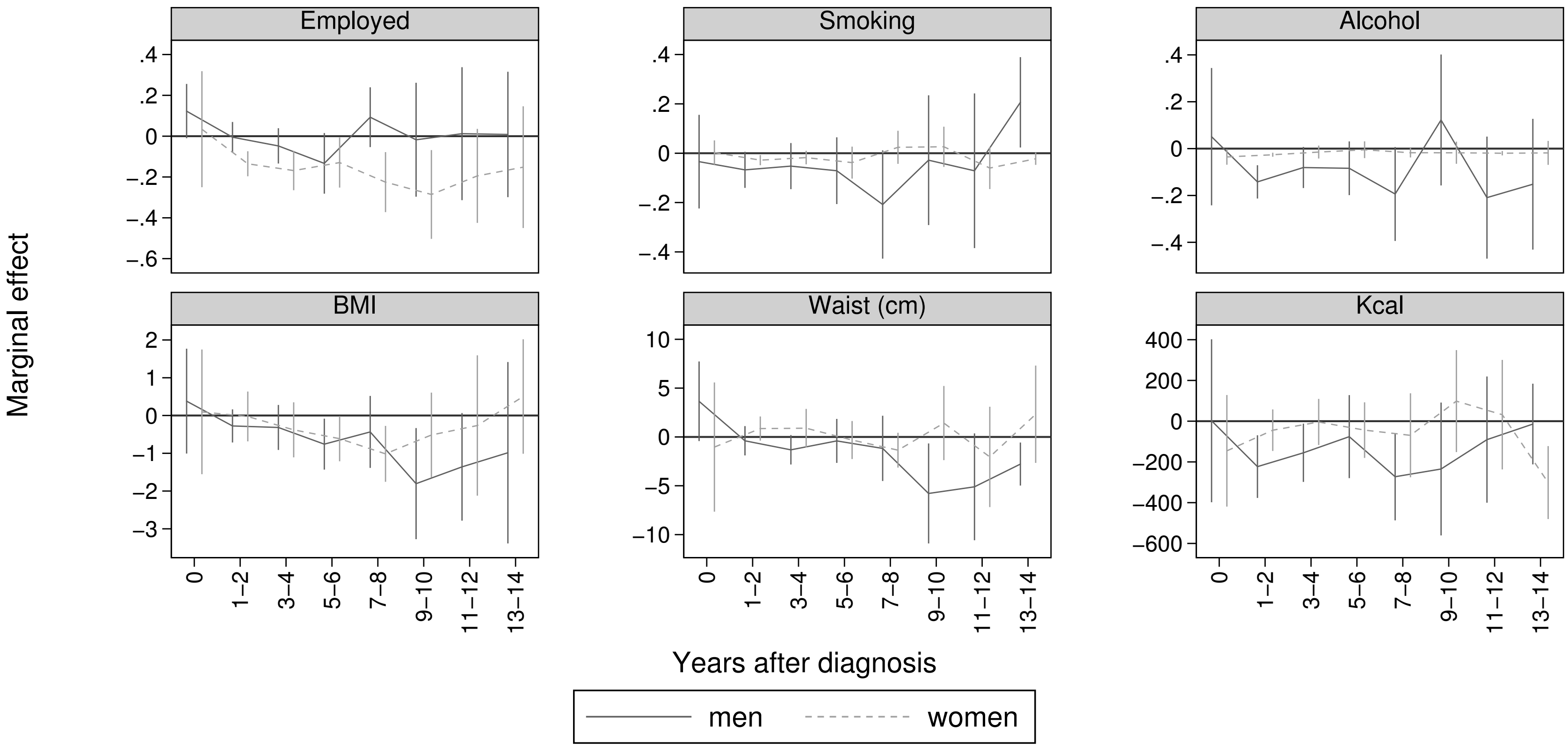


Figure 0.5: The effect of time since diabetes diagnosis on employment status and behavioural outcomes (duration groups, random effects)



0.4 Disussion

The evidence for the impact of a diabetes diagnosis on employment chances and behavioural risk factors remains scarce, in particular in MICs, where diabetes has become a mayor contributor to the burden of disease. We added to this evidence by exploring these relationships using longitudinal data from China, also improving upon previous methodology by taking into account the potential relationship over time between 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. We did, however, not find similar changes in behavioural risk factors for women. 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 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 robustness checks using 'naive' regression in the form of RE models further indicated 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 risk behaviours (smoking and alcohol consumption) and caloric intake.

0.4.1 Limitations

The study has several limitations. While we used two estimation methods to reduce the influence of selection bias due to unobserved confounding, they are still unable 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 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). Given that the FE estimates were close to those of the MSMs, 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 the selection into diabetes due to some form of baseline values, be it via demeaning as in the FE model—and thereby accounting for all time-invariant confounding—or by using baseline values as in the 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 prevent or delay debilitating complications. Fourthly, a diagnosis may also introduce 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 the role of each of these factors in affecting employment chances and behavioural risk factors. Only for the reductions in smoking and alcohol consumption, it seems reasonable to attribute them to diagnosis induced awareness to reduce these risk factors.

0.4.2 Potential mechanisms

There are various pathways that may explain the observed patterns in the effects of a diabetes diagnosis on employment and behavioural risk factors for males and females.

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 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 (Yang and Weng, 2014). Importantly, 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 less 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 affected 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 more likely to not access care due to lower income levels than men. 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 (Peters, Huxley, Sattar, et al., 2015; Peters, Huxley, and Woodward, 2014a,b). Women are more likely to have spend more time in a pre-diabetes state (Bertram and Vos, 2010) and to cross the threshold only once the metabolic has significantly deteriorated, leading to a greater risk of cardiovascular disease and stroke (Peters, Huxley, Sattar, et al., 2015). Supporting this, a study for China found a greater prevalence of diabetes comorbidities in Chinese women than 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 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 to a greater extent.

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 female employment probabilities (Harris, 2009; Latif, 2009; Minor, 2011; Seuring, Serneels, et al., 2016)—often more than for men. Most comparable to our results is likely a study from Mexico which also used FE and data for a similar time period and for a MIC that also experienced a rapid epidemiological transformation towards a very high diabetes burden (Seuring, Serneels, 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 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 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, indicating a positive relationship. This underlines the importance of accounting for unobserved heterogeneity.

0.5 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. 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 greater emphasis needs to be put on reducing the burden of diabetes for women if the observed inequities in the diabetes impact shall be reduced.

Attrition

Table 0.5: 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%

Stabilized weights

Table 0.6: 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 0.7: 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 Other control variables: age, 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).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Table 0.8: 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 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 0.9: 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 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).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Robustness checks

MSMs using truncated weights

Table 0.10: 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 0.11: Effect of time since diabetes diagnosis on employment status and behavioural outcomes using MSM with truncated stabilized weights (1st and 99th percentile; imputed)

	(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 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).

Results using non-imputed data

Table 0.12: 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)

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/RE: N=22135 (male sample), N=23143 (female sample), MSM: N=10006 (male sample), N=11471 (female sample).

Table 0.13: Analysis of the effect of time 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 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/RE: N=22117 (male sample), N=23130 (female sample), MSM: N=10028 (male sample), N=11465 (female sample).

Table 0.14: 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	0.000	−.043	0.131	−1.013**	−3.347	−782.090***
	(.)	(.153)	(.156)	(.450)	(2.116)	(177.206)
Female sample						
0	0.123	0.000	0.000	−.136	−1.772	−101.086
	(.188)	(.)	(.)	(1.488)	(5.608)	(203.293)
1-2	−.083	−.018**	−.053*	−.613	−.685	−40.447
	(.067)	(.009)	(.028)	(.489)	(1.026)	(65.853)
3-4	0.000	0.000	0.000	−5.530*	−8.510***	0.676
	(.)	(.)	(.)	(3.260)	(1.787)	(257.875)

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 0.15: 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 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=22117 (male sample), N=23130 (female sample).

Table 0.16: 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 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=22117 (male sample), N=23130 (female sample).

Overweight and obesity results

Table 0.17: 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)

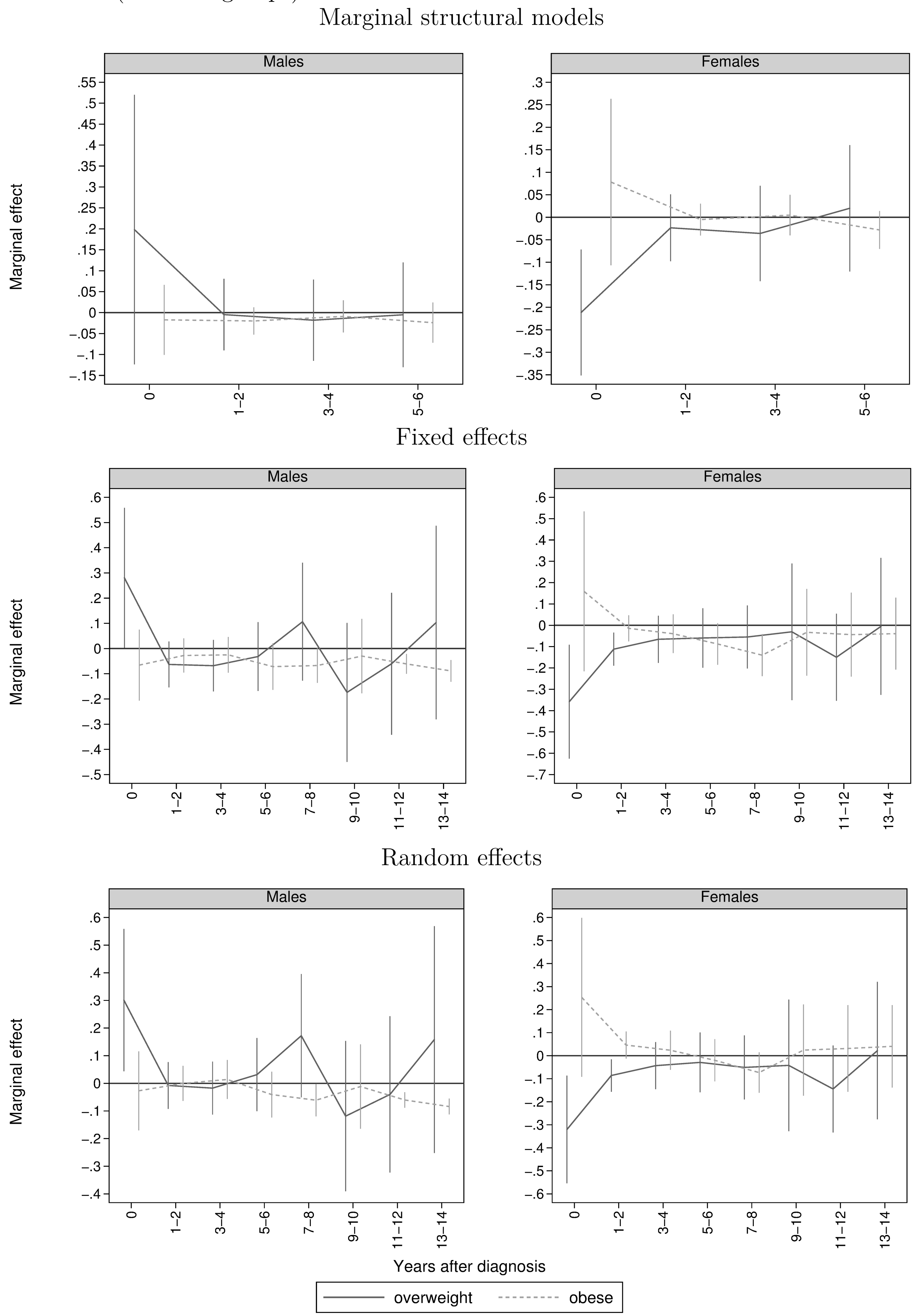
Notes Standard errors in parentheses. Other control variables: Age squared, region, urban, education, han, marital status, urbanization index, time dummies, health insurance status, household expenditures. FE/RE: N=23443 (male sample), N=23702 (female sample). MSM: N=16047 (male sample), N=16658 (female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

Table 0.18: 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 0.6: Analysis of the effect of time since diabetes diagnosis on overweight and obesity (duration groups)



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

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