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

Abstract

Recent evidence for Mexico suggests important differences in health status between people with diagnosed and undiagnosed diabetes. However, there is at best scarce evidence on the economic consequences of diabetes, especially in contexts where the condition often remains undiagnosed, as is typically the case in low- and middle income countries. Using Mexican longitudinal as well as biomarker data we estimated the impact of diabetes and diabetes duration on employment probabilities, wages and working hours. We further explored how these effects differed for those with diagnosed and undiagnosed diabetes. For the longitudinal analyses nationally representative data from 11836 men and 13745 women 15 to 64 years old were taken from three waves (2002, 2005, 2009) of the Mexican Family Life Survey. We estimated a fixed effects model to account for unmeasured time-invariant confounders of diabetes. We found a reduction in the probability of being employed of 5.4 and 5.9 percentage points for men and women, respectively, but no effects on hours worked or wages. Employment probabilities fell gradually with each year since diagnosis. Using cross-sectional biomarker data, we observed that 68% of those exhibiting glycated hemoglobin (HbA1c) levels above the clinical diabetes threshold did not self-report a diagnosis, hence were undiagnosed. Nevertheless, regression analysis revealed that there was no association of diabetes with labour outcomes for undiagnosed women or men. This suggests that results based on self-reported diabetes cannot be extended to the considerable population with undiagnosed diabetes, likely because of a selection of people in worse health and with a longer diabetes duration into the diagnosed population. An earlier diagnosis and improved treatment of diabetes therefore may prevent adverse health effects and related economic hardship in Mexico.

Keywords: diabetes, employment, instrumental variable, Mexico

1. Introduction

Diabetes, a disease characterized by elevated blood glucose levels due to the body's inability to use insulin properly, has in the last two decades increasingly become a global problem, with over two-thirds of people with diabetes living in low- and middle-income countries (LMICs) (International Diabetes Federation 2015). In Mexico, diabetes prevalence has grown from 6.7% in 1994 to 14.4% in 2006 (Barquera, Campos-Nonato, et al. 2013) and 15.8% in 2015. Diabetes has become the number one contributor to mortality (International Diabetes Federation 2015), by increasing the risk for heart disease and stroke, blindness, kidney disease and neurologic problems, foot ulcers and amputations (Reynoso-Noverón et al. 2011). However, via effective self-management of the disease through regular monitoring, behaviour change and medication adherence, the occurrence of complications could be avoided or delayed in many cases (Gregg et al. 2012; Lim et al. 2011).

The observed increase in diabetes incidence has been attributed to a deterioration in diet and a reduction in physical activity (Barquera, Hernandez-Barrera, et al. 2008; Basu et al. 2013), while genetic predisposition among Mexicans with pre-Hispanic ancestry may also play a role (Williams et al. 2013). The onset of diabetes has been occurring at an ever earlier age in Mexico (Bello-Chavolla et al. 2017), increasing the risk of complications occurring during the productive lifespan. Only a minority of patients in Mexico achieves adequate blood glucose control (Barquera, Campos-Nonato, et al. 2013). Moreover, diabetes is related to diseases, including depression, hypertension and cardiovascular disease that impose a heavy burden onto the health system (World Health Organization 2016).

Despite the catastrophic impact of diabetes on health, its economic consequences, in particular in LMICs, have received little attention. This applies in particular to the evidence on the effects of diabetes on labour outcomes (Seuring, Archangelidi, et al. 2015). In high-income countries substantial economic losses have been observed (Brown, Pagán, et al. 2005; Brown, Perez, et al. 2011; Brown 2014; Latif 2009; Minor 2011, 2013; Mi-

nor and MacEwan 2016). A rare LMIC study exploited a natural experiment in China and found a significant reduction in income due to a recent diabetes diagnosis (Liu and Zhu 2014). A study for Mexico, using cross-sectional data from 2005, found a significant ($p<0.01$) reduction in employment probabilities for males by 10 percentage points (p.p.) and for females by 4.5 p.p. ($p<0.1$) (Seuring, Goryakin, et al. 2015). Most existing studies relied on instrumental variable (IV) estimation, using the genetic component of diabetes based on its family history, to address the potential endogeneity of diabetes. However, family history of diabetes may also proxy for other genetically transferred traits, including unobserved abilities, as well as intrahousehold or intergenerational dynamics that impact labour outcomes directly; the validity of this IV therefore remains debatable. Panel data methods provide the opportunity to account for time-invariant unobserved individual characteristics, which may play an important role, but—to the best of our knowledge—have not yet been used. Such unobservables, for instance hunger or nutrient deficiency experienced in early life, could adversely affect health as well as the propensity to develop type 2 diabetes later in life (Ewijk 2011; Li et al. 2010; Sotomayor 2013). Additionally, there may also be long-term effects on labour outcomes—either directly through reductions in contemporaneous productivity (Currie and Vogl 2013), or indirectly by limiting educational attainment and human capital accumulation (Ayyagari et al. 2011). These unobservables thereby present a major source of a potential bias that can be accounted for by panel data estimation.

In parallel to these identification challenges, heterogeneity in impact and measurement across the population also deserves further investigation. Recent evidence from Mexico points to a strong positive relationship of diabetes duration with mortality due to diabetes related complications (Herrington et al. 2018). A longer disease duration was found to be related with higher glycated hemoglobin (HbA1c) levels, and undiagnosed diabetes had the lowest diabetes related mortality risks. The latter points to potential selection issues when using self-reported diabetes data to investigate economic outcomes. Those who

self-report, and hence tend to be diagnosed, are in worse health than those undiagnosed. This can lead to an overestimation of the economic effects of diabetes, in particular in populations with a large undiagnosed population, such as in many LMICs (Beagley et al. 2014). So far, however, little evidence exists on the economic impact according to diabetes severity, duration or for those with undiagnosed diabetes.

The objective of this study was to provide new evidence on the impact of diabetes on labour outcomes, adding to previous work by paying close attention to the challenges of unobserved heterogeneity, to the chronic nature of diabetes and to undiagnosed diabetes. We used three waves of the Mexican Family Life Survey (MxFLS), covering the period 2002–2012. Applying a fixed effects model we accounted for time-invariant heterogeneity when assessing the impact of self-reported diabetes and time since diagnosis on labour outcomes. To assess the role of undiagnosed diabetes we used biomarker data from the last wave of the MxFLS.

2. Data

This paper used data from the Mexican Family Life Survey (MxFLS), a nationally representative longitudinal household survey, containing three waves conducted in 2002, 2005–2006 and 2009–2012. It is the only longitudinal household survey in Mexico that provides data on a wide range of social, demographic, economic and health characteristics (Rubalcava and Teruel 2013). Because the survey followed participants moving within Mexico as well as to the US, around 90% of the original sample have been reinterviewed in the third wave. Our samples were restricted to the working age population (15–64) and excluded pregnant women. Pregnant women have an increased diabetes risk and may not be able to work. Since their inclusion may have biased the estimates, we dropped all observations of women reporting to be pregnant at the time of the survey (N=764). We also dropped those reporting to be in school. The first part of the analysis used all three waves, ex-

ploiting the panel structure of the data. The second part used a biomarker subsample of the third wave (2009–2012). Because the biomarker sample included everybody above the age of 44, but only a random subsample of those aged 44 or below (Crimmins et al. 2015), its age structure was older and hence its self-reported diabetes prevalence higher. The analysis therefore compares with self-reported data for this specific subsample only.

Our outcome variables of interest were employment status, weekly working hours, hourly wage, and occupation. Employment status was defined as having carried out an activity that helped with the household expenses the last week while working for at least four hours per week. We explicitly included informal employment and employment without monetary remuneration, for instance in family businesses. Hourly wage was constructed as reported monthly income from the first and second job, divided by average number of weeks per month and weekly working hours. Labour income was obtained from the response to questions on wages, income from piecework, tips, income from extra hours, meals, housing, transport, medical benefits and other earnings, or from the response to a question on aggregate labour income for the entire month. We adjusted calculated wages for inflation in the year of interview and considered the log of real wages. Due to a considerable number of missing or zero income reports, the sample used for the wage estimation was smaller than the sample for working hours. Working hours were combined from both the first and a potential second job. Descriptive statistics for the entire panel sample show that over 80% of men with diabetes and 87% of men without diabetes reported some form of employment, compared to 26% of women with diabetes and 37% of women without diabetes (see Table 1). Interestingly, men did not report considerably higher hourly wages than women but worked more hours per week. There were also little differences in working hours and wages between men and women with and without diabetes. Men worked more often in agricultural jobs while women were more likely to be self-employed or in non-agricultural wage employment. The educational attainment of women was lower than that for men on average. Similarly, those without

diabetes were better educated than those with diabetes. Further, the diabetes sample is about 15 years older on average than the non-diabetes sample, both for men and women.

The first part of the analysis focused on the relationship of labour outcomes with self-reported diabetes, which was based on the survey question: "Have you ever been diagnosed with diabetes?". Because the data did not distinguish between type 1 and type 2 diabetes, we assumed that the estimates represented the impact of type 2 diabetes, by far the most common type of diabetes in Mexico. As a robustness check, we re-estimated our main results categorizing diabetes into early-onset and late-onset cases, according to the age at which diabetes was first reported in the survey. This was a similar approach to Alegre-Díaz et al. (2016), who assumed that everybody diagnosed before age 35 and using insulin had type 1 diabetes. Accordingly, we assumed that those first reporting a diabetes diagnosis before the cut-off had type 1 diabetes while those above had type 2 diabetes. Nonetheless, because we cannot warranty that this is 100% accurate (as it may be unlikely that both populations consisted exclusively of one type of diabetes) we preferred to think of the groups as of early- and late-onset groups. This separation also provides information about the effects for different age groups, as the late-onset group had an average age of onset of 50 compared to 28 for the early-onset group. In the pooled data, which combines all three waves, diabetes was self-reported by 5% of men and 6% of women. This is consistent with other reports from Mexico for the time, showing a prevalence of diagnosed diabetes of 7.5% in 2006 in a sample also including people over the age of 64 (Barquera, Campos-Nonato, et al. 2013). Apart from self-reported diabetes, which was available in all rounds, we also used information on the self-reported year of diagnosis as well as biometrically measured HbA1c levels for a subsample of respondents from the third wave.

Information on the self-reported year of diagnosis, reported in the third wave, allowed us to construct a measure of time since diagnosis. For those also present in previous waves, we inferred the time since diagnosis by the difference between the year of the interview and the year of diagnosis. This allowed us to use panel data methods for the duration

analysis as well, however limited to those reporting the year of diagnosis in the third wave.

The second part of the analysis assessed the role of undiagnosed diabetes. The biometrically measured blood glucose value that allowed us to identify those with undiagnosed diabetes, was available for over 6000 respondents in the third wave. We used the internationally recognized cut-off of an HbA1c $\geq 6.5\%$ to define diabetes as recommended by the World Health Organization (WHO) (World Health Organization 2011). As we show in Supplementary Table S6, 19% of self-reported diabetes cases had HbA1c levels below the diabetes threshold. We dropped those for our analysis as it was not clear if they had misreported their diabetes status or had achieved these low levels as a result of their successful disease management. Analysis including those cases led to qualitatively similar results (results available on request).

3. Estimation strategy

To investigate the relationship between self-reported diabetes and three labour outcomes—employment, weekly working hours and wages—we estimated a fixed effects model. The fixed effects model accounts for the potential bias introduced by time-invariant unobservables, providing an estimate of the effect for cases that received a diagnosis throughout the survey.

$$Y_{it} = \beta_0 + \beta_1(D_{it} - \overline{D}_i) + \beta_2(X_{it} - \overline{X}_i) + \beta_3\overline{D}_i + \beta_4\overline{X}_i + (u_i + e_{it}), \quad (1)$$

The fixed effects model uses only the within-person variation for identification, i.e. the difference between the diabetes indicator D_{it} and its cluster mean $\overline{D}_i$, so that β_1 represented the within-person variation of diabetes over time. The same applies to the other time-varying covariates X_{it}. Y_{it} was a binary variable taking a value of 1 if respondent i reported being in employment at time t and 0 otherwise. For ease of interpretation we chose to estimate a linear probability model for the effects of diabetes on employment.

To estimate the effect on working hours and wages, our empirical models were estimated conditional on being in employment. Y_{it} represented the log hourly wage or the weekly working hours over the last year, for respondent i at time t.

We also included time variant confounders—as the fixed effects model accounts for time invariant confounding only. We controlled for changes in the level of urbanization, the level of education, the state of residence, marital status, the number of children below the age of six in the household, a quadratic age term and calendar year dummies. We also control for household wealth approximated by a household asset index. We composed an indicator using principal component of household assets and housing following Filmer et al. (2001) (Filmer and Pritchett 2001). The asset index reflected owning a vehicle, a second house, a washing machine, dryer, stove, refrigerator or furniture, any electric appliances, any domestic appliances, a bicycle, farm animals, and accounted for the physical condition of the house, proxied by the type of floor material and water access. In our main regression models we did not account for body mass index (BMI). While part of the effect of diabetes may be due to potential adverse effects of obesity, including BMI as a control variable in the model would have led to attenuated estimates if the diagnosis of diabetes also had an effect on BMI, which has been shown to be the case in other studies (De Fine Olivarius et al. 2015; Seuring, Suhrcke, et al. 2018; Slade 2012). Similarly, we did not control for any diseases that were likely consequences of diabetes, such as heart disease or other micro- and macro-vascular complications (World Health Organization 2016), as this would prevent any causal interpretation of the relationship of diabetes with our labour market outcomes (Angrist and Pischke 2009). Nonetheless, we carried out a robustness analysis controlling for obesity. Stata 15 was used for all analyses (StataCorp 2017).

3.1. Labour outcomes and time since diagnosis

The chronic nature and irreversibility of diabetes provide good reason to explore the long term effects post diagnosis. To do this we replaced the binary diabetes indicator of

Eq 1 with a continuous variable indicating years since the diagnosis was first reported. Simultaneous inclusion of year dummies and time since diagnosis (which varies by one unit in each time period) would typically not allow separate identification of the coefficient of time since diagnosis. In this case, identification relied on the presence of people without diabetes in the sample, for which diabetes duration did not increase.

We also considered a spline function that allowed for non-linear effects over time, with $g(Dyears_{it}) = \sum_{n=1}^{N} \delta_n \cdot max\{Dyears_{it} - \eta_{n-1}\} I_{in}$ and $I_{in} = 1[\eta_{n-1} \leq Dyears_{it} < \eta_n]$, with η_n being the place of the n-th node for $n = 1, 2, \ldots, N$. The coefficient δ_n captured the effect of diabetes for the n-th interval. The effects are linear if $\delta_1 = \delta_2 =, \ldots, = \delta_n$.

Based on visual inspection (Fig. 1 on page 1) we chose three nodes located at 3, 7 and 12 years after diagnosis. The first three years should capture any immediate effects of the diagnosis, the years four to seven any effects during time of adaptation to the disease and the later terms the long term effects. We also estimated a non-linear model using dummy variables for duration groups rather than splines, applying the same duration cut-offs. Because the year of diagnosis was only reported in the third wave, time since diagnosis was not available for those who were not interviewed in the third round. A reported diagnosis in the year of the interview was counted as 'one year since diagnosis'.

3.2. Labour outcomes and biometrically measured diabetes

The biomarker analysis consisted of three steps. We first re-estimated Eq 2 to assess the relationship between self-reported diabetes with labour outcomes, but this time for the cross-sectional biomarker sample only, using the following specification:

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 X_i + c_i + v_i \tag{2}$$

where v_i were community fixed effects, which reflected local unobserved characteristics, such as access to healthcare, poverty and unemployment in the community. Communities

(or *localidades* in Spanish) are the smallest administrative units (nested within municipalities) recognized by the Mexican Institute for Statistics and Geography (INEGI). We did not use household fixed effects since the average number of observations per household was close to one.

In a second step we estimated the relations between biomarker diabetes and labour outcomes, using the following equation:

$$Y_i = \beta_0 + \beta_1 Dbio^d + \beta_2 X_i + v_i + u_i, \tag{3}$$

where $Dbio^d$ was equal to 1 if HbA1c $\geq 6.5\%$.

To estimate the effect of undiagnosed diabetes, we added self-reported diabetes back into the equation (Eq 4).

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 Dbio_i + v_i + u_i. \tag{4}$$

This changed the interpretation of $Dbio_i$, which now reflected the effect on those with undiagnosed diabetes, i.e. the respondents not self-reporting diabetes but with HbA1c levels equal to or above the threshold.

We further investigated the effect of the severity of diabetes on labour outcomes, replacing $Dbio$ with $Dbio^c$, a variable that was 0 for HbA1c $< 6.5\%$ and increased by one for every percentage point increase in HbA1c for those with an $HbA1c \geq 6.5\%$ (Eq 5). This allowed us to investigate the effect of a one percentage point increase in HbA1c levels for people with undiagnosed diabetes (β_2) as well as for those with self-reported diabetes (β_3).

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 Dbio_i^c + \beta_3 Dsr_i * HbA1c_i + \beta_4 X_i + v_i + u_i. \tag{5}$$

4. Results

4.1. Labour outcomes and self-reported diabetes

The results of estimating Eq 1 in Table 2 indicated statistically significant reductions in the probability of employment for men and women with self-reported diabetes. Employment probabilities were reduced by 5.4 p.p. for men and 5.9 p.p. for women. There was no significant relationship between diabetes and working hours or wages.

Dividing the diabetes population into early and late onset groups, men, and potentially also women, saw their employment probabilities negatively affected by a diabetes onset later in life (Supplementary Table S2). In particular, women with an early diabetes onset experienced an adverse effect. For working hours, effects were less precise but may indicated increased working hours for men with an early diabetes onset, while women reduced their work hours. Finally, we found higher wages for women with an early diabetes onset, but no effects for men.

To assess whether diabetes affected the selection into different types of work, we investigated the role of diabetes for the probability of being in non-agricultural wage employment, agricultural employment or self-employment. We found a reduction in the probability to work in agriculture for women, but not for men (Table 3). Disaggregating the diabetes groups further according to their age showed that most statistically significant relationships were driven by the older-onset group (Supplementary Table S3). For male self-employment, diabetes increased the probabilities to be self-employed in the younger group, while it reduced the probabilities to be self-employed in the older-onset group.

We reestimated all regressions in this section including a binary control for obesity (BMI $\geq$ 30) (Supplementary Table S7 and Table S8). This led to a reduction in sample size due to the larger number of missing cases for BMI. Obesity itself did not appear to be an independent predictor of any labour market outcome. The estimates of the effect of diabetes remained similar for most outcomes. Only for male employment probabilities,

the diabetes coefficient was no longer statistically significant at the 10 percent significance level. Estimating the original model without accounting for obesity, but using the sample with only non-missing BMI cases, showed similar changes in effects (results available on request).

4.2. Labour outcomes and time since diagnosis

Fig. 1 shows that the probability of employment for men steadily declined as time progressed, using a non-parametric kernel-weighted local polynomial regression. For women, a first drop-off occurred right after diagnosis; though no consistent pattern emerged thereafter. The dynamics for working hours and wages were less clear, with a possibly long term negative trend for women but not for men.

Table 4 panel A shows the results of estimating Eq **??**, which indicated that male and female employment probabilities fell every year, with a larger effect shown by the within coefficient.

Wages were reduced for women as diabetes progressed using the linear specification. Using diabetes onset groups, there was no evidence of an effect of diabetes duration for early onset groups (see Supplementary Table S4). Unfortunately the very limited number of diabetes cases in the early-onset group prohibited the estimation of effects of early diabetes onset duration on wages and working hours.

The non-linear results for the spline function and dummy variable approach are presented in panels B and C, respectively. They suggest that the main adverse effects appeared after more than seven years since diagnosis. The same was true for female wages. Re-estimating the specifications with a random effects model showed that, at least for the models with dummies, an immediate reduction in employment probabilities that became stronger the longer a person had diabetes (see Supplementary Table S5). Note that we did not estimate models splitting diabetes in early and late onset groups, as this implied strong reductions in statistical power.

Controlling for obesity, results remained very similar and obesity itself was not found to be affecting any labour market outcome (Supplementary Table S9).

4.3. Cross-sectional biomarker analysis

As reported in Supplementary Table S6, 18% of the observations in the biomarker sample were undiagnosed, which accounts for 68% of all cases above the diabetes threshold. Comparing the health status and diabetes risk factors of the diagnosed and undiagnosed diabetes populations suggested that those with self-reported diabetes were older and in worse health, both objectively and subjectively, compared to those undiagnosed.

Table 6 presents the results from estimating Eq. 2 – 5. Panel A confirms the earlier longitudinal results using self-reported diabetes for the cross-sectional biomarker sample. The results in panel B indicate that the relationship with employment became weaker when using diabetes defined by the biomarker instead of self-reported diabetes, in particular for men. Results in Panel C were obtained from estimating Eq. 4 and indicate an absence of a (statistically significant) negative relationship between undiagnosed diabetes and labour outcomes.

To explore whether the adverse effects increased with higher HbA1c levels, we estimated Eq. 5. The results in panel D only show a borderline statistically significant adverse association of 0.9 percentage points per percentage point increase in HbA1c for female employment probabilities.

5. Discussion

Diabetes is now one of the most common chronic diseases in LMICs, as well as high-income countries (HICs), with potential severe impacts on the health and economic well-being of those affected. Yet rigorous evidence on the economic consequences for LMICs remains scarce.

To address key methodological challenges, this paper used rich longitudinal panel data from Mexico that also contained diabetes biomarkers. The biomarker data showed alarming levels of clinically tested diabetes (27% prevalence) and indicate that a large proportion of the Mexican population (18%) has undiagnosed diabetes.

The paper provided evidence for adverse effects of self-reported diabetes on employment, working hours and wages. While earlier work showed evidence for Mexico for employment (Seuring, Goryakin, et al. 2015), this paper presented, by our knowledge, the first evidence on the relationship of diabetes, working hours and wages. Furthermore, we added to the study of Seuring, Goryakin, et al. (2015) by using longitudinal instead of cross-sectional data to identify a causal relationship. We provided first evidence of the long term impact of diabetes in Mexico and explored the extent and effects of undiagnosed diabetes. We confirmed the findings of Seuring, Goryakin, et al. (2015) insofar that we found an adverse effect of diabetes on male employment. We further showed more conclusive evidence that also women experience a reduction in their employment probabilities due to diabetes. Taking into account the differences in employment between men and women, the found effects translate into relative reductions of their employment probabilities of 6% for men and 14% for women. We also found that the effects were mainly driven by those with a diabetes onset at a relatively later state, consisting of older people with most likely type 2 diabetes. This was also found by Seuring, Goryakin, et al. (2015) in their stratified analysis of an older and younger age group. Analyses of the long term impact indicated that the employment probability fell gradually in the years following diagnosis. The results using a non-linear model were less clear, potentially due to reductions in statistical power, but suggested that adverse effects became stronger with time since diagnosis. The linear effect contrasts with estimates for the USA, where such an effect was absent; however allowing for non-linearity, revealed falling employment probabilities after 11 to 15 years for females and after 2-5 years for males (Minor 2013).

Overall, a relationship of diabetes and working hours or wages was mostly absent.

Although any explanation at this point is speculative, it may be that higher paid and more educated individuals were able to remain employed without experiencing wage reductions, for instance due to their particular set of skills. They may also have had access to better health care leading to better diabetes related health outcomes. Low paid workers, on the other hand, may have lacked access to quality diabetes care, making it more likely that they developed severe complications earlier (Flores-Hernández et al. 2015). They may also have been more likely to be in informal employment and low skilled jobs with less job security, and thus more prone to being laid off and replaced with healthier workers.

We found that self-reported diabetes cases were not representative of the entire diabetes population in Mexico. A large share of people with diabetes were undiagnosed and significantly healthier and younger, suggesting a selection into the diagnosed group based on the severity and duration of diabetes. Consequently, diabetes as defined by the HbA1c threshold, was less related to reduced employment probabilities compared to self-reported diabetes. Further analysis showed that this was due to the absence of an association between undiagnosed diabetes and employment. These results are similar to those found for the USA, where no statistically significant relationship was observed between undiagnosed diabetes on employment, while a significant effect of diagnosed diabetes was observed (Minor and MacEwan 2016). Our results further indicated that the difference in employment effects of diagnosed and undiagnosed diabetes was not mediated by current HbA1c levels. This is similar to findings for Mexican-Americans in the USA, where employment outcomes were unrelated to higher HbA1c levels (Brown, Perez, et al. 2011). A possible explanation may be that HbA1c levels are primarily informative for the last three months, and are not the only or best indicator for the severity of diabetes. Overall, it seems that a longer diabetes duration with its related health consequences, and selection into the diagnosed population based on emerging diabetes related health problems, could have been driving the adverse economic effects among those with a self-reported diagnosis.

Our study had several limitations. While our model accounted for any time-invariant

confounding, the estimates may have been affected by unobserved time-variant confounders. Reverse causality, where employment status affects the propensity to develop or be diagnosed with diabetes, may also have played a role. Existing studies that looked at this particular direction of causality, however, have not found strong evidence for an effect of employment status on diabetes (Bergemann et al. 2011; Schaller and Stevens 2015), though they were carried out in HICs. We did not control for the effects of obesity, hypertension, self-reported health or other diseases in our models due to the high probability that they were affected by diabetes themselves, which would have made a causal interpretation of the estimates more difficult. Robustness checks including obesity indicated that our main findings remained mostly unchanged and that any occurring changes were likely the result of a smaller sample size rather than of the inclusion of obesity. For the duration analysis an additional limitation, imposed by the data, was that the year of diagnosis was only reported in the third wave. While this still allowed us to construct an estimate of the time since diagnosis for the previous waves, it restricted the analysis to those that were present in the last wave. Finally, we used a WHO recommended HbA1c cut-off to diagnose diabetes, due to the lack of a Mexico specific cut-off. There is some evidence that HbA1c may be affected by ethnicity (Sacks 2011). Hence, if Mexican ethnicity would lead to different HbA1c levels, the use of our cut-off could have led to misclassification based on the used biomarkers.

Despite these limitations, our findings bear important implications. First, the impact of self-reported diabetes on labor outcomes in Mexico seemed mostly limited to its effect on employment probabilities. Second, its effect on employment was much stronger for females, though the underlying reasons for this remain unclear. Potential explanations are that lower working hours or wages for women make a dropout less costly. Other evidence suggests that women with diabetes are in worse metabolic health compared to men when they cross the diabetes threshold (Peters et al. 2015), making it more likely for them to drop out. Third, caution is needed when estimates based on self-reported diabetes

are interpreted in terms of the entire population, i.e. extending to those with undiagnosed diabetes. Ideally, studies would include a biomarker analysis, acknowledge the differences between diagnosed and undiagnosed sub-populations, and carry out a separate analysis whenever feasible. If this is not possible, study conclusions about the effects of self-reported diabetes should be limited to this specific part of the population. This is of particular importance in LMICs where the share of undiagnosed diabetes is often high.

The large proportion of previously undiagnosed cases found in this paper indicates that diagnosis—at least in Mexico—happens late or not at all. This may reduce the possibilities to prevent complications via treatment and self-management, increasing the risk of severe complications appearing premature. Earlier diagnosis and ensuing effective treatment may lighten the health and economic burden. Therefore, more research is needed to investigate the economic impact of diabetes over time. Longitudinal biomarker information could be used to observe the true duration and severity of diabetes as well as the time that passes till a medical diagnosis. This would allow for a better understanding of when adverse economic effects start to appear. Further, future research should investigate how time of diagnosis and treatment of diabetes affect the occurrence of adverse labour market effects of diabetes. The results of such research could allow costing studies to include more detailed information on the indirect costs of diabetes; or inform cost-effectiveness analyses that aim to include a measure of the potential benefit of the intervention to employers or society at large.

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Supplementary material

Strategies to deal with inconsistent self-reporting over time

Reporting error can pose a considerable challenge in the use of self-reported data. Fortunately, the MxFLS data provide several possibilities to assess the amount of misreporting and apply corrections before estimating the labour market effects of diabetes. In what follows we describe how we have dealt with inconsistencies in self-reported diabetes over time.

Throughout the surveys, self-reported diabetes was measured by the question 'Have you ever been diagnosed by diabetes'. One of the key advantages of panel data is the repeated measurement which results in more than one data point, allowing to uncover inconsistencies for cases with multiple observations. Very little is known about inconsistencies in self-reported diabetes over time. Zajacova et al. (2010) assess the consistency of a self-reported cancer diagnosis over time in the USA. The study found that 30% of those who had reported a cancer diagnosis at an earlier point, failed to report the diagnosis at a later point in time. A more recent diagnosis was found to be reported with greater consistency, possibly due to increasing recall problems as time since diagnosis advanced.

When assessing the MxFLS, we also found inconsistencies in the diabetes self-reports across the three waves, with between 10–20% of those reporting diabetes in one wave not doing so in one of the subsequent waves. To improve the validity of diabetes self-reports, we were interested in reducing the amount of reporting inconsistencies.

For diabetes, the main concern with mismeasurement is related to a lack of a diagnosis. Wrong self-reports indicating a diagnosis of diabetes we deemed less of a problem since incentives to falsely report a diabetes diagnosis seem to be very limited—although we cannot exclude this. A study from China found that the vast majority (98%) of those who self-reported diabetes were tested positive for diabetes, while only a minority of those who were tested positive for diabetes (40%) actually self-reported the disease (Yuan et al.

2015). Our data showed a similar pattern, with a low proportion (2%) of the respondents being tested negative while self-reporting diabetes, while the majority of those who were tested positive (68%) did not self-report diabetes.

We used the above information to infer the "true" diabetes status for those with inconsistent reports. For respondents present in all three waves, we corrected inconsistencies as reported in Supplementary Table S1. We assumed that if diabetes was reported only once in the first two waves (either in 2002 or 2005) and then not reported again in the ensuing waves, this diabetes report was likely to be false (see lines 3 and 4 in Supplementary Table S1) and that the person never had received a diagnosis. If a diabetes diagnosis was reported in two of the three waves (in 2002 and 2009 but not 2005, or in 2002 and 2005 but not in 2009), we assumed that the respondent had diabetes in all three waves (see lines 1 and 2 in Supplementary Table S1). For cases where we only had information from two waves, we assumed that if a diabetes diagnosis had been reported in a prior wave they also had diabetes in the ensuing wave, even if it was not reported in the latter (see lines 5 and 6 in Supplementary Table S1), given that most diabetes self-reports tend to be correct.

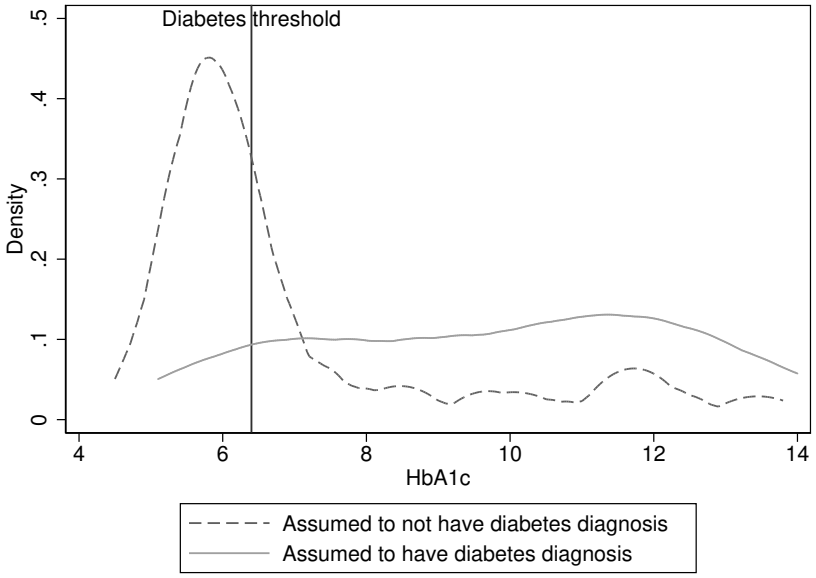
Table S1. Inconsistencies in diabetes self-report in MxFLS.

	Inconsistency	Assumption	Number of observations replaced
1	Diabetes self-report only in 2002, but not in 2005 and 2009	Has no diabetes in 2002 either	66
2	Diabetes self-report only in 2005, but not in 2002 and 2009	Has no diabetes in 2005 either	52
3	Diabetes self-report in 2002, 2005 but not in 2009	Has diabetes in 2009 as well	19
4	Diabetes self-report in 2002, 2009 but not in 2005	Has diabetes in 2005 as well	63
5	Diabetes self-report in 2002, but not in 2005. Not in survey in 2009	Has diabetes in 2005 as well	44
6	Diabetes self-report in 2005, but not in 2009. Not in survey in 2002	Has diabetes in 2009 as well	23

We then tested if the respondents we categorized as not having a diabetes diagnosis based on above rules, were actually more likely to not have biometrically measured diabetes, using the biomarker data from wave 3. Of those with inconsistencies in their diabetes self-reports, 95 were present in the biomarker sample (46 with two self-reports (from lines 3 and 4 in Table S1) and 49 with one self-report of diabetes (from lines 1 and 2 in Supplementary Table S1)). Supplementary Figure S1 illustrates the difference between

both groups and suggests that indeed those with two self-reports of diabetes were much more likely to have HbA1c values above the diabetes threshold. A t-test comparing the mean HbA1c for the two groups indicated that those with two self-reports also had significantly ($p<0.001$) higher HbA1c levels than those with only one self-report of diabetes (9.7% vs. 7.1%). Further, of those with one self-report, only 30% had an HbA1c$\geq$ 6.5% compared to 87% of those with two self-reports. Based on these results it appears that we did minimize misclassification of people into diabetes or no diabetes.

Figure S1: Kernel density of HbA1c values for those with one inconsistent and two inconsistent reports.



Early versus late onset of diabetes

Table S2. **Labour outcomes and self-reported diabetes by diabetes onset.**

	Employment		Weekly working hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Early onset	0.133	-0.206^{**}	14.856^{*}	-18.250^{*}	-0.490	0.375^{***}
	(0.176)	(0.086)	(8.329)	(9.515)	(0.337)	(0.057)
Late onset	-0.059^{**}	-0.047^{*}	-0.936	-1.346	0.071	0.074
	(0.026)	(0.025)	(1.510)	(2.553)	(0.068)	(0.161)
N	21388	27339	13828	7068	17616	9112

Notes Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3. **Selection into types of work and self-reported diabetes by diabetes onset.**

	Non-agric.		Agriculture		Self-employed	
	Males	Females	Males	Females	Males	Females
Early onset	0.030	−0.105	−0.226	−0.068	0.328**	−0.027
	(0.216)	(0.074)	(0.139)	(0.047)	(0.161)	(0.048)
Late onset	−0.007	0.007	−0.001	−0.018**	−0.054**	−0.029
	(0.029)	(0.019)	(0.022)	(0.009)	(0.026)	(0.019)
N	20719	26575	20719	26575	20719	26575

Notes Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4. **Relationship between self-reported years since diagnosis and employment probabilities using continuous duration by diabetes onset.**

	Employment		Monthly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Early onset	−0.005	0.007				
	(0.017)	(0.013)				
Late onset	−0.012**	−0.008**	0.088	0.303	−0.007	−0.059***
	(0.005)	(0.004)	(0.275)	(0.505)	(0.013)	(0.022)
N	16308	22450	13592	7394	10778	5748

Notes The effects of early onset diabetes on wages and working hours could not be estimated due to no within-variation for diabetes. Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Random effects model

Table S5. **Relationship between self-reported years since diagnosis and employment probabilities using continuous duration and duration splines (random effects).**

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Panel A: linear effect						
Years since diagnosis	−0.007***	−0.004***	0.039	−0.130	0.010**	−0.009
	(0.002)	(0.001)	(0.102)	(0.127)	(0.005)	(0.008)
Panel B: splines						
Years since SR diagnosis						
0–3	−0.008	−0.015**	−0.035	0.507	0.038**	0.034
	(0.006)	(0.006)	(0.346)	(0.614)	(0.017)	(0.029)
4–7	0.001	0.004	0.242	−0.570	−0.032	−0.048
	(0.011)	(0.011)	(0.665)	(1.062)	(0.032)	(0.052)
8–12	−0.008	0.002	−0.116	−0.080	−0.003	−0.074
	(0.015)	(0.011)	(0.855)	(1.098)	(0.041)	(0.050)
13+	−0.012	−0.004	0.035	−0.339	0.029	0.011
	(0.008)	(0.003)	(0.410)	(0.241)	(0.018)	(0.017)
Panel C: dummies						
0–3	−0.036*	−0.041**	−0.821	1.091	0.134**	0.021
	(0.021)	(0.021)	(1.154)	(1.826)	(0.054)	(0.083)
4–7	−0.014	−0.056**	0.877	1.200	0.093	−0.003
	(0.022)	(0.023)	(1.375)	(2.530)	(0.059)	(0.118)
8–12	−0.069*	−0.043	0.427	0.302	−0.070	−0.148
	(0.037)	(0.030)	(2.288)	(2.995)	(0.101)	(0.117)
13+	−0.121***	−0.043	−0.568	−2.104	0.242*	−0.279*
	(0.045)	(0.031)	(2.280)	(3.088)	(0.126)	(0.153)
N	16308	22450	13592	7394	10778	5748

Notes Panel A presents the results of the linear specifications. Panel B presents the results of the non-linear specifications. Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S6. **Number of observations with diabetes (HbA1c $\geq$ 6.5%) and self-reported diabetes.**

	$HbA1c < 6.5\%$	HbA1c $\geq$ 6.5%	Total
No self-reported diabetes (N)	4544	1181	5725
Row %	79%	21%	100%
Cell %	**71%**	**18%**	-
Self-reported diabetes (N)	129	554	683
Row %	19%	81%	100%
Cell %	**2%**	**9%**	-
Total (N)	4673	1735	6408

Robustness checks

Table S7. **Labour outcomes and self-reported diabetes controlling for obesity**

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Obese (BMI $\geq$ 30)	0.007	−0.005	−0.127	−1.144	0.018	0.082
	(0.012)	(0.013)	(0.773)	(1.188)	(0.038)	(0.061)
Diabetes	−0.046	−0.064**	−0.689	−0.169	0.036	0.033
	(0.028)	(0.027)	(1.772)	(2.904)	(0.078)	(0.183)
N	17992	24145	14866	7929	11711	6166

Notes Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S8. **Selection into types of work and self-reported diabetes controlling for obesity.**

	Males			Females		
	Non-agric.	Agric.	Self-employed	Non-agric.	Agric.	Self-employed
Obese (BMI $\geq$ 30)	0.005	−0.032**	0.036***	−0.021*	0.003	0.010
	(0.017)	(0.013)	(0.014)	(0.011)	(0.004)	(0.009)
Diabetes	0.010	0.002	−0.060**	−0.011	−0.020**	−0.025
	(0.033)	(0.023)	(0.028)	(0.020)	(0.010)	(0.021)
N	17414	17414	17414	23458	23458	23458

Notes Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S9. **Relationship between self-reported years since diagnosis and employment probabilities using continuous duration and duration splines and controlling for obesity.**

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Panel A: linear effect						
Obese (BMI $\geq$ 30)	0.003	−0.010	0.059	−0.412	0.026	0.035
	(0.012)	(0.014)	(0.831)	(1.247)	(0.040)	(0.064)
Years since diagnosis	−0.019***	−0.008	0.259	−0.008	−0.016	−0.073**
	(0.006)	(0.006)	(0.375)	(0.721)	(0.019)	(0.034)
Panel B: splines						
Years since SR diagnosis						
Obese (BMI $\geq$ 30)	0.003	−0.009	0.073	−0.371	0.027	0.036
	(0.013)	(0.014)	(0.832)	(1.247)	(0.040)	(0.064)
0–3	−0.014	−0.022	0.806	3.762	−0.070	0.015
	(0.015)	(0.017)	(1.051)	(3.169)	(0.057)	(0.139)
4–7	−0.003	0.009	−0.293	−3.921**	0.035	−0.121
	(0.018)	(0.015)	(0.914)	(1.811)	(0.044)	(0.108)
8–12	−0.023	0.001	−0.098	3.082*	−0.062	−0.085
	(0.022)	(0.016)	(1.350)	(1.736)	(0.066)	(0.074)
13+	−0.038**	−0.024*	0.855	−1.128	0.005	−0.065
	(0.017)	(0.012)	(1.029)	(1.421)	(0.053)	(0.063)
Panel C: dummies						
Obese (BMI $\geq$ 30)	0.005	−0.009	0.044	−0.378	0.026	0.031
	(0.012)	(0.014)	(0.831)	(1.245)	(0.040)	(0.064)
0–3	0.028	−0.032	1.484	22.434*	0.047	−0.658
	(0.059)	(0.065)	(3.825)	(11.579)	(0.212)	(0.622)
4–7	0.001	−0.054	2.399	12.909	0.013	−0.793
	(0.044)	(0.055)	(3.181)	(11.063)	(0.154)	(0.616)
8–12	−0.064	0.010	0.296	15.604	−0.293	−1.125*
	(0.069)	(0.066)	(4.994)	(11.038)	(0.247)	(0.583)
13+	−0.208**	−0.073	−1.966	17.459*	0.168	−1.090**
	(0.105)	(0.081)	(4.975)	(10.262)	(0.256)	(0.499)
N	13912	19972	11622	6487	9262	5054

Notes Panel A presents the results of the linear specifications. Panel B presents the results of the non-linear specifications. Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Tables

Table 1. **Descriptive statistics for the panel sample (2002,2005,2009).**

	Males			Females		
	No diabetes	Diabetes	p (t-test)	No diabetes	Diabetes	p (t-test)
Dependent variables						
Employed	0.87	0.80	0.00	0.37	0.26	0.00
Hourly wage (in Mexican Peso)	42.29	46.79	0.83	40.67	36.33	0.61
Weekly working hours	46.83	46.51	0.60	39.06	37.51	0.09
Non-agricultural worker or employee	0.51	0.41	0.00	0.24	0.13	0.00
Agricultural worker	0.19	0.13	0.00	0.02	0.01	0.00
Self-employed	0.16	0.26	0.00	0.09	0.11	0.04
Diabetes variables						
Diabetes duration (years)		7.40			7.79	
Control variables						
Age	35.31	50.68	0.00	35.37	50.45	0.00
Any medical insurance	0.47	0.59	0.00	0.50	0.62	0.00
City of 2,5oo-15,000	0.11	0.09	0.03	0.11	0.13	0.00
City of 15,000-100,000	0.10	0.14	0.00	0.10	0.10	0.40
City of >100,000	0.34	0.39	0.00	0.35	0.34	0.47
Married	0.53	0.77	0.00	0.53	0.66	0.00
Number of children (age<6) in household	1.49	1.14	0.00	1.60	1.13	0.00
Indigenous group	0.19	0.15	0.00	0.19	0.19	0.86
Education						
Secondary	0.31	0.22	0.00	0.31	0.16	0.00
High school	0.16	0.07	0.00	0.14	0.03	0.00
Higher education	0.11	0.12	0.39	0.10	0.03	0.00
Wealth index	0.00	0.04	0.27	−0.01	0.01	0.36
N	20391	994		25664	1666	

Notes Mean values. Diabetes refers to self-reported diabetes.

Table 2. **Labour outcomes and self-reported diabetes.**

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Diabetes	-0.054^{**}	-0.059^{**}	-0.506	-1.998	0.055	0.081
	(0.025)	(0.024)	(1.499)	(2.511)	(0.068)	(0.158)
N	21388	27339	17616	9112	13828	7068

Notes Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. **Selection into types of work and self-reported diabetes.**

	Males			Females		
	Non-agric.	Agric.	Self-employed	Non-agric.	Agric.	Self-employed
Diabetes	−0.006	−0.008	−0.043	−0.001	−0.022**	−0.029
	(0.029)	(0.022)	(0.026)	(0.018)	(0.009)	(0.018)
N	20719	20719	20719	26575	26575	26575

Notes Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. **Relationship between self-reported years since diagnosis and employment probabilities using continuous duration and duration splines.**

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Panel A: linear effect						
Years since diagnosis	−0.016***	−0.009*	0.185	0.115	−0.016	−0.067**
	(0.006)	(0.005)	(0.334)	(0.652)	(0.018)	(0.029)
Panel B: splines						
Years since SR diagnosis						
0–3	−0.013	−0.018	0.708	2.953	−0.005	0.047
	(0.014)	(0.016)	(0.857)	(2.700)	(0.054)	(0.124)
4–7	−0.011	−0.002	0.215	−2.517	−0.032	−0.131
	(0.014)	(0.014)	(0.761)	(1.752)	(0.046)	(0.101)
8–12	0.003	−0.003	−1.153	1.144	−0.009	−0.053
	(0.021)	(0.014)	(1.252)	(1.635)	(0.065)	(0.061)
13+	−0.039***	−0.015	0.720	0.184	−0.007	−0.096***
	(0.014)	(0.010)	(0.943)	(1.414)	(0.057)	(0.037)
Panel C: dummies						
0–3	0.005	−0.007	0.352	17.309*	0.223	−0.447
	(0.052)	(0.059)	(3.123)	(9.975)	(0.186)	(0.549)
4–7	−0.031	−0.049	2.860	10.878	0.047	−0.568
	(0.042)	(0.050)	(2.664)	(9.504)	(0.127)	(0.544)
8–12	−0.066	−0.026	−0.709	13.733	−0.133	−0.873*
	(0.063)	(0.059)	(4.181)	(9.695)	(0.207)	(0.521)
13+	−0.134	−0.062	−3.379	13.309	0.164	−0.882**
	(0.098)	(0.068)	(4.715)	(9.239)	(0.284)	(0.446)
N	16298	22427	10771	5746	13583	7391

Notes Panel A presents the results of the linear specifications. Panel B presents the results of the non-linear specifications. Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. **Descriptive comparison of diagnosed and undiagnosed population with diabetes.**

	Males			Females		
	Diagnosed diabetes	Undiagnosed diabetes	P value (t-test)	Diagnosed diabetes	Undiagnosed diabetes	P value (t-test)
Employed	0.811	0.877	0.019	0.233	0.329	0.002
Hourly wage	35.280	30.939	0.220	37.242	32.822	0.495
Usual weekly working hours	44.562	46.682	0.166	31.838	39.788	0.004
Age	53.258	45.530	0.000	53.544	45.388	0.000
Any medical insurance	0.691	0.589	0.009	0.717	0.645	0.025
City of 2,5oo-15,000	0.092	0.105	0.593	0.116	0.114	0.916
City of 15,000-100,000	0.147	0.090	0.021	0.079	0.093	0.447
City of >100,000	0.332	0.290	0.267	0.292	0.329	0.250
Married	0.751	0.663	0.018	0.629	0.588	0.221
Number of children (<15) in household	0.972	1.138	0.110	0.934	1.250	0.001
Indigenous group	0.171	0.216	0.159	0.192	0.209	0.534
Primary	0.484	0.450	0.406	0.635	0.479	0.000
Secondary	0.212	0.230	0.594	0.126	0.230	0.000
High school	0.060	0.115	0.022	0.031	0.105	0.000
Higher education	0.147	0.109	0.147	0.025	0.071	0.003
Wealth index	−0.213	0.141	0.000	0.033	0.104	0.314
Subjective health						
very good	0.014	0.092	0.000	0.013	0.044	0.010
good	0.184	0.431	0.000	0.173	0.370	0.000
fair	0.664	0.446	0.000	0.635	0.533	0.002
bad	0.129	0.027	0.000	0.170	0.047	0.000
very bad	0.009	0.004	0.374	0.009	0.004	0.344
Glycated hemoglobin (HbA1c)	9.635	8.531	0.000	9.781	8.699	0.000
Hypertension (self-reported)	0.258	0.078	0.000	0.384	0.157	0.000
Blood pressure						
Systolic	136.475	130.981	0.001	136.426	123.516	0.000
Diastolic	84.562	82.448	0.025	84.912	80.019	0.000
Heart disease (self-reported)	0.032	0.008	0.013	0.041	0.025	0.178
BMI	28.989	28.385	0.128	30.573	30.058	0.234
Obese (BMI $\geq$ 30)	0.374	0.333	0.301	0.500	0.470	0.388

Notes Mean values. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

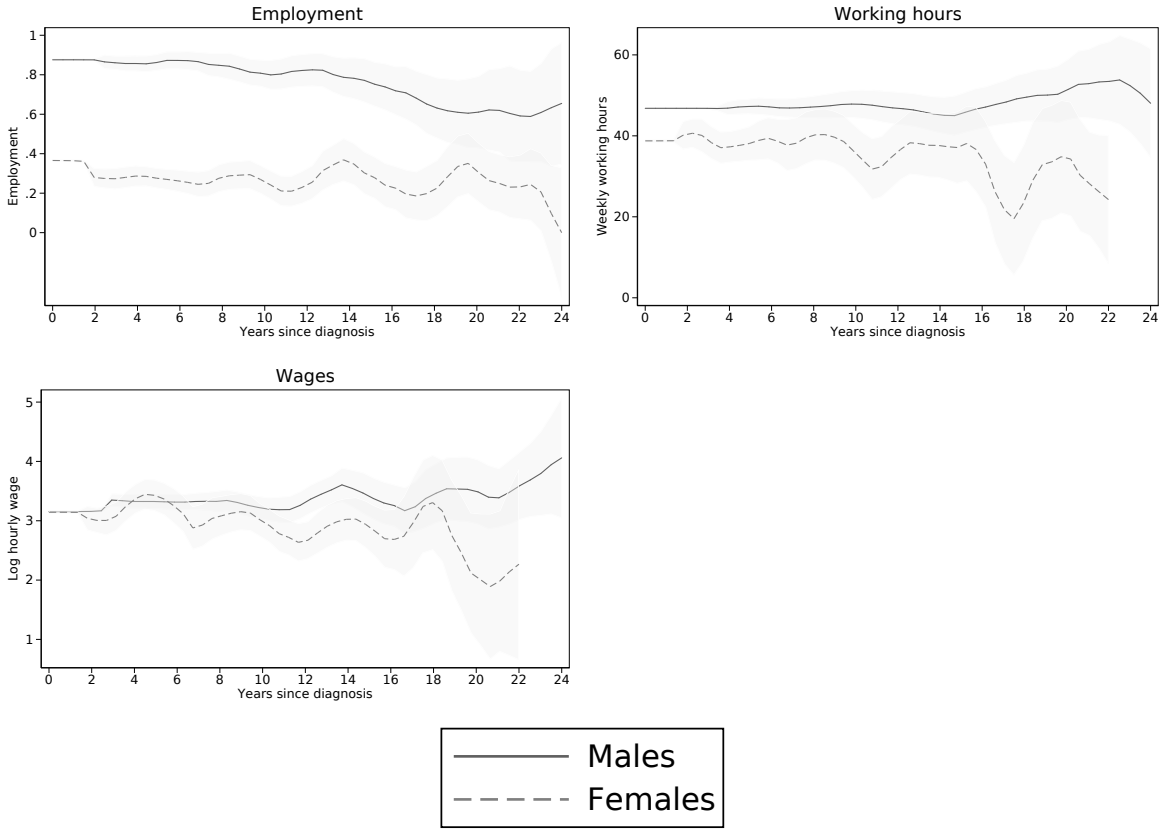
Table 6. **Biomarker results.**

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Panel A: Diabetes (self-reported)						
Self-reported diabetes	−.057**	−.057**	−.543	−2.154	−.057	−.005
	(.025)	(.026)	(1.427)	(2.433)	(.070)	(.121)
Panel B: Diabetes (biomarker)						
Biomarker diabetes (HbA1c $\geq$ 6.5)	−.013	−.034*	0.018	1.382	−.005	−.045
	(.016)	(.018)	(.849)	(1.480)	(.045)	(.071)
Panel C: Self-reported and undiagnosed diabetes						
Self-reported diabetes (β_1)	−.061**	−.042	−.715	−3.954	−.067	0.034
	(.028)	(.031)	(1.574)	(2.823)	(.085)	(.137)
Undiagnosed diabetes (HbA1c $\geq$ 6.5) (β_2)	0.006	−.020	0.224	2.394	0.014	−.053
	(.018)	(.020)	(.962)	(1.647)	(.050)	(.078)
Panel D: HbA1c levels						
Self-reported diabetes	−.080*	−.066	0.084	−4.463	−.061	0.011
	(.046)	(.046)	(2.409)	(4.592)	(.107)	(.227)
HbA1c if $\geq$ 6.5	0.005	−.009*	−.150	0.318	0.004	−.005
	(.005)	(.006)	(.253)	(.463)	(.014)	(.019)
Self-reported diabetes × HbA1c if $\geq$ 6.5	0.003	0.010	−.064	0.375	−.002	−.000
	(.012)	(.012)	(.668)	(1.043)	(.030)	(.052)
N	2749	3537	2276	1121	1787	866

Notes Results are based on community level fixed effects. Robust standard errors in parentheses. All models include variables for states, urbanization, level of education, marital status, number of children < 6, wealth, health insurance status, age squared and one dummy variable for each calendar year to account for the multiple years of data collection for the third wave. The wage and working hour models additionally control for type of work (agricultural and self employed with non-agricultural wage employment as the base). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figures

Figure 1: Employment, wages, working hours and years since self-reported diabetes: Kernel-weighted local polynomial regression



Notes The shaded areas indicate the 95% confidence intervals.