

¹ The impact of diabetes on labour market outcomes in
² Mexico: a panel data and biomarker analysis

³

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 aware and those unaware of their 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 within-between effects model to account for unmeasured time-invariant confounders of diabetes while simultaneously assessing differences between subjects with and without diabetes. The within effects indicated a reduction in the probability of being employed between 5.4 and 6.0 percentage points for men and women, respectively, but no effects on hours worked or wages. The between effects showed similar results. 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.

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 problem for low- and middle-income countries (LMICs) as well as high-income countries (HICs), with over two-thirds of people with diabetes living in the developing world (International Diabetes Federation 2015). In Mexico, diabetes prevalence is estimated to have grown from 6.7% in 1994 to 14.4% in 2006 (Barquera 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 nerve problems, food ulcers and amputations (Reynoso-Noverón et al. 2011). However, via effective self-management of the disease, many if not all of the complications can be avoided (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 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 et al. 2013). Moreover, diabetes in Mexico coexist with high levels of infectious diseases, exposing the health system to a 'double-disease burden' increasing the pressure to identify treatment priorities and use existing resources efficiently (Gutiérrez-delgado et al. 2009).

Despite the catastrophic impact of diabetes on health, its economic consequences, in particular in LMICs have received less attention, especially its effects on labour outcomes (Anonymous 2007). The latter have been studied predominantly in high-income countries, where substantial economic losses have been observed (H. S. Brown et al. 2005, 2011; T. T. Brown 2014; Latif 2009; Minor 2011, 2013; Minor et al. 2016). For LMICs less evidence

58 is available. One study exploited a natural experiment in China and found a significant
 59 reduction in income due to a recent diabetes diagnosis (Liu et al. 2014). A study for
 60 Mexico, using cross-sectional data from 2005, found a significant ($p < 0.01$) reduction in
 61 employment probabilities for males by 10 percentage points (p.p.) and for females by 4.5
 62 p.p. ($p < 0.1$) (Anonymous 2007). Most existing studies rely on instrumental variable (IV)
 63 estimation to address the potential endogeneity of diabetes using the genetic component of
 64 diabetes based on its family history as an instrument. However, family history of diabetes
 65 may also proxy for other genetically transferred traits, including unobserved abilities, as
 66 well as intrahousehold or intergenerational dynamics that impact labour outcomes directly;
 67 the validity of this IV therefore remains debatable. Panel data methods provide the
 68 opportunity to account for time-invariant unobserved individual characteristics, which may
 69 play an important role, but have not yet been used by our knowledge. Such unobservables,
 70 like for instance health endowments could adversely affect health as well as the propensity
 71 to develop type 2 diabetes in particular (Ewijk 2011; Li et al. 2010; Sotomayor 2013); they
 72 may also affect labour outcomes—either directly through their effects on contemporaneous
 73 productivity (Currie et al. 2013), or indirectly by limiting educational attainment and
 74 human capital accumulation (Ayyagari et al. 2011). These unobservables thereby present
 75 a major potential source of bias that can be accounted for by the use of panel data
 76 estimation.

77 In parallel to these identification challenges, heterogeneity in impact and measurement
 78 across the population also deserves further investigation. Recent evidence from Mexico
 79 points to a strong positive relationship of diabetes duration with mortality due to diabetes
 80 related complications (Herrington et al. 2018). A longer disease duration was found to
 81 be related with higher glycated hemoglobin (HbA1c) levels and undiagnosed diabetes had
 82 the lowest diabetes related mortality risks. The latter points to potential selection issues
 83 when using self-reported diabetes data to investigate economic outcomes as those who
 84 self-report, and hence tend to be diagnosed, are in worse health than those undiagnosed,

85 potentially leading to an overestimation of the economic effects of diabetes, in particular
86 in populations with a large undiagnosed population, such as in many LMICs (Beagley
87 et al. 2014). So far, however, little evidence exists on the economic impact according to
88 diabetes severity and duration or for those with undiagnosed diabetes.

89 The objective of this study was to provide new evidence on the impact of diabetes on
90 labour outcomes, adding to previous work by paying close attention to the challenges of
91 unobserved heterogeneity, to the chronic nature of diabetes and to the population unaware
92 of their condition (i.e. the 'undiagnosed'). We used three waves of Mexican panel data,
93 covering the period 2002–2012. Applying a within-between model, which models individual
94 fixed effects and between effects separately, we accounted for time-invariant heterogeneity
95 when assessing the impact of self-reported diabetes and time since diagnosis on labour
96 outcomes. We also used rich and novel biomarker data from the most recent wave of data,
97 we assessed the role of undiagnosed diabetes.

98 2. Data

99 This paper uses data from the Mexican Family Life Survey (MxFLS), a nationally represen-
100 tative longitudinal household survey, containing three waves conducted in 2002, 2005–2006
101 and 2009–2012. Data was collected on a wide range of social, demographic, economic and
102 health characteristics (Rubalcava et al. 2013). Our samples were restricted to the working
103 age population (15–64) and excluded those in school and pregnant women (N=764) due to
104 their increased diabetes risk and pregnancy related changes in employment. The first part
105 of the analysis used all three waves and the panel structure of the data. The second part
106 used a biomarker subsample of the third wave (2009–2012). Because the biomarker sample
107 included everybody above the age of 44, but only a random subsample of those aged 44
108 or below (Crimmins et al. 2015), its age structure was older and hence its self-reported
109 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 and 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 86% of men reported some form of employment compared to 37% of women (see Table 1). Interestingly, men did not report considerably higher hourly wages than women but worked more hours per week. Men also more often worked 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.

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?”. If we encountered inconsistencies in the self-report of diabetes over time, we used information from previous and ensuing waves to infer the true diabetes status (see Supplementary Table S1 for more detail). 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

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)
<i>Dependent variables</i>						
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
<i>Diabetes variables</i>						
Diabetes duration (years)		7.40			7.79	
<i>Control variables</i>						
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 2,500-15,000	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	

Mean values. Diabetes refers to self-reported diabetes.

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, similar 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 likely type 1 diabetes while those above had likely type 2 diabetes. Unfortunately, we lacked detailed information on the type of treatment to also take into account the use of insulin. As a result, we preferred to think of the groups as early- and late diabetes onset groups (in the case of the within-coefficient, which only takes into account incident cases). Because we lacked information about the exact age at diagnosis diabetes cases in the first two waves, the between coefficient may also stratify people with diabetes into the late onset group even though they actually had early onset diabetes, but joined the sample with an already existing diagnosis. In the pooled data,

which combines all three waves, diabetes was self-reported by 5% of men and 6% of women, respectively. 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 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 measurement error associated with self-reported diabetes. This was done by also considering those with undiagnosed diabetes, i.e. the false negatives. 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.

3. Estimation strategy

To investigate the relationship between self-reported diabetes and three labour outcomes—employment, wages and weekly working hours—we estimated a within-between (WB) effects model, an extension of the correlated random effects model first proposed by Mundlak (1978), that explicitly models both within and between effects (Bell et al. 2015). The within effects are identical to a fixed effects (FE) model, accounting for the potential bias introduced by time-invariant unobservables, providing an estimate of the effect for cases that received a diagnosis throughout the survey (705 incident cases compared to 970 non-changing diabetes cases in the used sample). Modeling the between effect allowed us to

also use information from those that already had diabetes at baseline.

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

The within-effect is arrived at by the difference between the diabetes indicator D_{it} and its cluster mean \bar{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} . Cluster means of diabetes and of all other time-varying covariates were also included to capture the between effect. The error terms u_i and e_{it} capture the errors for the within and between variation, respectively. Y_{it} was a binary variable taking a value of 1 if respondent i reported being in employment at time t and 0 otherwise. Making use of the user written Stata command `xthybrid` (Schunck et al. 2017), we estimated WB effects applying a multilevel mixed-effects generalized linear model. For ease of interpretation we chose to estimate a linear probability model for the effects of diabetes on employment.

For the outcomes 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 .

The regressions controlled for level of urbanization, education, state, marital status, the number of children below the age of 6 in the household, a quadratic age term, calendar year dummies as well as household wealth. We composed an indicator using principal component of household assets and housing following Filmer et al. (2001). We did not account for body mass index (BMI) as this would have led to biased estimates if the diagnosis of diabetes also had an effect on BMI, which was likely to be the case (De Fine Olivarius et al. 2015; Slade 2012). In general, control variables should not also be potential outcome variables (Angrist et al. 2009), hence we also did not control for other chronic diseases that may have been caused by diabetes. 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 estimated the following model:

$$Y_{it} = \beta_0 + \beta_1(Dyears_{it} - \overline{Dyears}_i) + \beta_2(X_{it} - \overline{X}_i) + \beta_3\overline{Dyears}_i + \beta_4\overline{X}_i + (u_i + e_{it}), \quad (2)$$

where $Dyears_{it}$ was continuous indicating years since the diagnosis was first reported. While 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 Eq. 2 and Eq. 3, identification here 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.

$$Y_{it} = \beta_0 + \beta_1(Dsplines_{it} - \overline{Dsplines}_i) + \beta_2(X_{it} - \overline{X}_i) + \beta_3\overline{Dsplines}_i + \beta_4\overline{X}_i + (u_i + e_{it}), \quad (3)$$

Based on visual inspection (Fig. 1 on page 15) we chose three nodes located at three, seven and twelve years after diagnosis to capture short-, immediate- and 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. 4 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:

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 X_i + c_i + v_i \quad (4)$$

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

$$Y_i = \beta_0 + \beta_1 Dbio_i^d + \beta_2 X_i + v_i + u_i, \quad (5)$$

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

To estimate the effect of undiagnosed diabetes, we added self-reported diabetes and interacted it with the biomarker (Eq. 6).

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 Dbio_i + \beta_3 Dsr_i * Dbio_i + \beta_4 X_i + v_i + u_i. \quad (6)$$

Note that the interaction term changes the interpretation of β_1 and β_2 , with β_1 now representing the effect on those aware of their condition but with HbA1c levels below the diabetes threshold; while β_2 reflects 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. The interaction term β_3 shows the effect for those with self-reported diabetes and HbA1c levels above the threshold.

We further investigated the effect of the severity of diabetes on labour outcomes, re-

placing $Dbio^d$ with $Dbio^c$, a variable that was 0 for $HbA1c < 6.5\%$ and took the actual value of $HbA1c$ for those with an $HbA1c \geq 6.5\%$ (Eq. 7). 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 above the diabetes threshold (β_3).

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 Dbio_i^c + \beta_3 Dsr_i * HbA1c_i + \beta_4 X_i + v_i + u_i. \quad (7)$$

4. Results

4.1. Labour outcomes and self-reported diabetes

The results of estimating Eq. 1 in Table 2 indicated significant and substantial reductions in the probability of employment for men and women with self-reported diabetes. The overall similarity of between estimates suggests that the within effect is generalizable to the entire self-reporting diabetes population, i.e. not only for representative of those that developed diabetes after joining the survey. Additionally, it provides suggestive evidence that time-invariant unmeasured confounders may play a limited role. Employment probabilities were reduced by over 5 p.p. for both genders, translating into relative reductions of 14% for women and of 6% for men. There was no significant relationship between diabetes on one hand and working hours and wages on the other, though the between estimates suggested that men with diabetes earned generally more than their counterparts without diabetes (Table 2). Overall these results thus suggested effects at the extensive margin (employment), but not at the intensive margin (labour supply and productivity).

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). For women, a particularly strong effect was also found for early diabetes onset. The between estimator suggested that men and women

with diabetes were less likely to be employed at older ages, but not at a younger age. For working hours, we only found an adverse effect using the within effects estimator for early onset, which may have been spurious due to low incidence rates of diabetes. For wages, we found a positive effect of diabetes incidence on women. However, the within estimates for early onset cases again may be spurious. The between estimates show that especially older men with diabetes received higher wages than those without diabetes.

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

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Diabetes (within)	-0.054** (0.025)	-0.060** (0.024)	-0.582 (1.501)	-1.990 (2.513)	0.063 (0.067)	0.074 (0.160)
Diabetes (between)	-0.077*** (0.016)	-0.066*** (0.015)	-0.804 (0.848)	-1.032 (1.306)	0.097** (0.046)	-0.078 (0.064)
Within=Between (p-value)	0.447	0.832	0.897	0.735	0.680	0.392
N	21388	27339	17616	9112	13828	7068

Robust standard errors in parentheses. All models control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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. The within effects estimator showed a reduction in the probability to work in agriculture for women, while we found no statistically significant effects for men. The between effects suggested that men with diabetes were less likely to be employed in agriculture, but more likely to be self-employed. Women with diabetes were less likely to be employed in agricultural and non-agricultural jobs (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). Interestingly, for male self-employment, incidence of 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. However, especially the results for early onset diabetes in women should be interpreted carefully due to limited number of diabetes

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

	Males			Females		
	Non-agric.	Agric.	Self-employed	Non-agric.	Agric.	Self-employed
Diabetes (within)	−0.007 (0.029)	−0.008 (0.022)	−0.042 (0.026)	−0.001 (0.018)	−0.022** (0.009)	−0.030* (0.018)
Diabetes (between)	−0.032 (0.020)	−0.090*** (0.014)	0.044** (0.019)	−0.049*** (0.012)	−0.008*** (0.003)	−0.012 (0.011)
Within=Between (p-value)	0.470	0.002	0.008	0.026	0.173	0.391
N	20719	20719	20719	26575	26575	26575

Robust standard errors in parentheses. All models control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

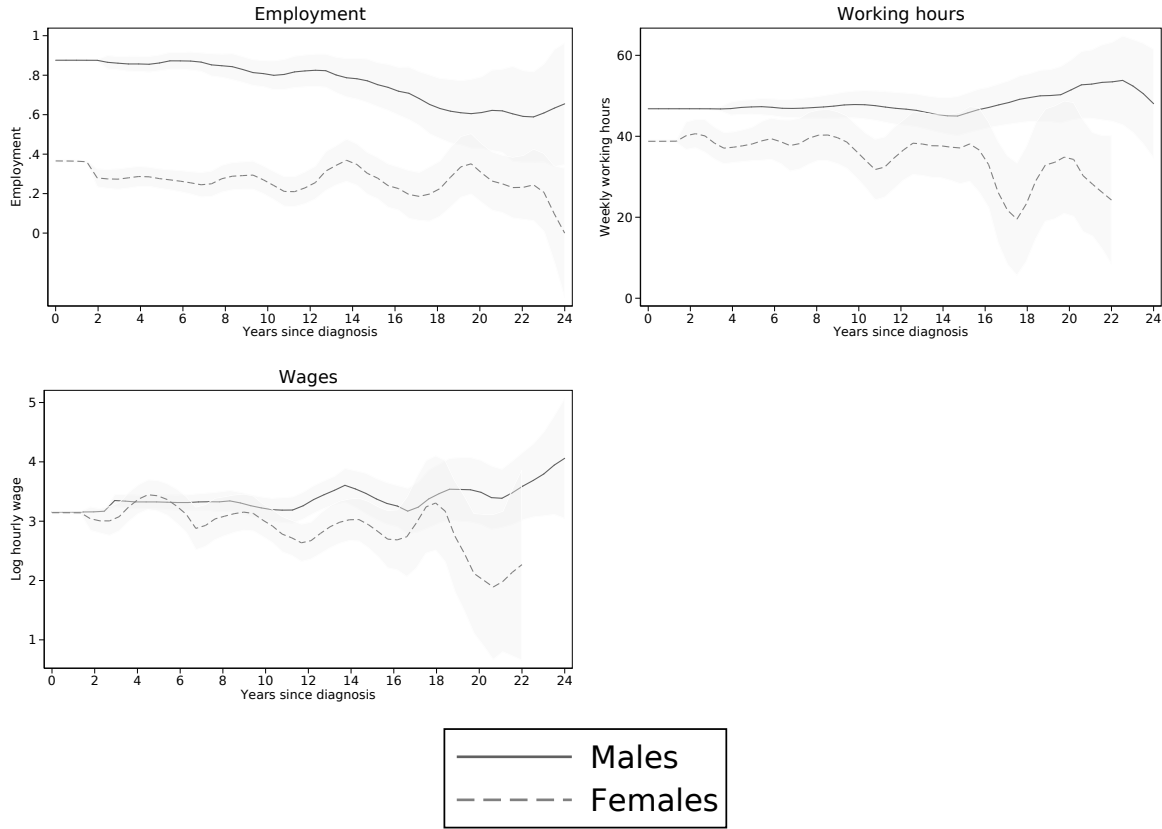
4.2. Labour outcomes and time since diagnosis

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. 2, which indicated that male and female employment probabilities fell every year, with a larger effect shown by the within coefficient.

For females, the within coefficient also suggested a reduction in wages as diabetes progressed while the between coefficient showed no association for women and a relatively small positive association with male wages. Using diabetes onset groups, there was no evidence of an effect of diabetes duration for early onset groups (see Supplementary Table S4). However, again the within results for early onset should be interpreted with caution due to the limited number of diabetes incidence cases in this group, which also prohibited the estimation of any within effects of early diabetes onset duration for wages and working hours. The results also indicated that the effects found in Table 4 were driven mainly by

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



The shaded areas indicate the 95% confidence intervals.

those with a diabetes onset after age 35.

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 a prolonged time of living with diabetes; i.e. after more than seven years since diagnosis. The same was true for female wages. The lack of a statistically significant effect for the earlier years of diabetes duration may have been due to a reduction in statistical efficiency as a result of the separation into duration groups and into within and between variation. Re-estimating the specifications with a random effects model that combined both types of variation into one estimate showed, at least for the models with dummies,

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 (within)	−0.016*** (0.006)	−0.009* (0.005)	0.185 (0.334)	0.115 (0.652)	−0.016 (0.018)	−0.067** (0.029)
Years since diagnosis (between)	−0.008*** (0.002)	−0.005*** (0.001)	−0.021 (0.107)	−0.140 (0.125)	0.010** (0.005)	−0.010 (0.009)
Within=Between (p-value)	0.139	0.482	0.560	0.696	0.165	0.061
Panel B: splines						
Years since diagnosis						
Within effects						
0–3	−0.013 (0.014)	−0.018 (0.016)	0.708 (0.857)	2.953 (2.700)	−0.005 (0.054)	0.047 (0.124)
4–7	−0.011 (0.014)	−0.002 (0.014)	0.215 (0.761)	−2.517 (1.752)	−0.032 (0.046)	−0.131 (0.101)
8–12	0.003 (0.021)	−0.003 (0.014)	−1.153 (1.252)	1.144 (1.635)	−0.009 (0.065)	−0.053 (0.061)
13+	−0.039*** (0.014)	−0.015 (0.010)	0.720 (0.943)	0.184 (1.414)	−0.007 (0.057)	−0.096*** (0.037)
Between effects						
0–3	0.005 (0.008)	0.010 (0.009)	−0.030 (0.465)	0.204 (0.653)	0.042** (0.020)	0.032 (0.032)
4–7	−0.003 (0.021)	−0.034 (0.023)	−0.444 (1.195)	0.727 (1.471)	−0.025 (0.052)	−0.034 (0.065)
8–12	−0.055** (0.023)	0.004 (0.024)	1.110 (1.367)	−1.525 (1.647)	−0.031 (0.060)	−0.109 (0.075)
13+	0.004 (0.008)	−0.004 (0.003)	−0.432 (0.476)	−0.282 (0.245)	0.034* (0.019)	0.015 (0.017)
Within=Between (p-value)	0.028	0.404	0.507	0.597	0.781	0.083
Panel C: dummies						
within effects						
0–3	0.005 (0.052)	−0.007 (0.059)	0.352 (3.123)	17.309* (9.975)	0.223 (0.186)	−0.447 (0.549)
4–7	−0.031 (0.042)	−0.049 (0.050)	2.860 (2.664)	10.878 (9.504)	0.047 (0.127)	−0.568 (0.544)
8–12	−0.066 (0.063)	−0.026 (0.059)	−0.709 (4.181)	13.733 (9.695)	−0.133 (0.207)	−0.873* (0.521)
13+	−0.134 (0.098)	−0.062 (0.068)	−3.379 (4.715)	13.309 (9.239)	0.164 (0.284)	−0.882** (0.446)
Between effects						
0–3	−0.002 (0.027)	0.033 (0.026)	−0.760 (1.370)	0.322 (1.944)	0.109* (0.057)	0.023 (0.091)
4–7	0.036 (0.030)	0.016 (0.042)	−1.004 (1.968)	3.157 (3.208)	0.154** (0.076)	0.082 (0.134)
8–12	−0.128** (0.065)	−0.199*** (0.055)	2.231 (3.111)	−0.792 (4.043)	−0.069 (0.131)	−0.197 (0.161)
13+	−0.187*** (0.050)	−0.076* (0.042)	−1.443 (2.895)	−4.127 (3.492)	0.196 (0.142)	−0.342** (0.173)
Within=Between (p-value)	0.397	0.060	0.672	0.242	0.721	0.745
N	16298	22427	10771	5746	13583	7391

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 control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

4.3. Cross-sectional biomarker analysis

As reported in Supplementary Table S6, 18% of the observations in the biomarker sample were false negatives, i.e. undiagnosed. Further, 2% were false positives, though the latter may have included cases that received a diabetes diagnosis and managed to reduce their HbA1c to non-diabetes levels via medication and/or lifestyle changes (Flores-Hernández et al. 2015). Overall 80% of the self-reports were consistent with the biomarker data and 27%. 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. This suggests a selection into the diagnosed group based on the severity and potentially duration of diabetes. If the adverse effects of diabetes are due to its health impact, we would suspect worse labour market outcomes for the diagnosed compared to the undiagnosed population.

Table 6 presents the results from estimating Eq. 4 – 7. 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. 6 and indicate an absence of a (statistically significant) negative relationship between undiagnosed diabetes (expressed in the 'Biomarker diabetes but not self-reported' coefficient) and labour outcomes. The coefficients for the interaction term were mostly negative, though only statistically significant in the case of female working hours.

To explore whether the adverse effects increased with higher HbA1c levels, we estimated

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	0.807	0.875	0.012	0.241	0.331	0.002
Hourly wage	35.931	30.670	0.120	36.092	32.638	0.550
Usual weekly working hours	44.341	46.682	0.104	34.708	39.681	0.046
Age	53.162	44.720	0.000	53.167	44.449	0.000
Any medical insurance	0.677	0.599	0.033	0.733	0.643	0.002
City of 2,500-15,000	0.096	0.107	0.643	0.112	0.112	0.994
City of 15,000-100,000	0.135	0.096	0.098	0.087	0.090	0.884
City of >100,000	0.331	0.297	0.325	0.294	0.333	0.185
Married	0.719	0.643	0.031	0.633	0.569	0.035
Number of children (age<6) in household	0.950	1.122	0.073	0.960	1.257	0.001
Indigenous group	0.158	0.211	0.079	0.195	0.207	0.626
Primary	0.479	0.434	0.238	0.626	0.465	0.000
Secondary	0.212	0.231	0.554	0.132	0.233	0.000
High school	0.062	0.131	0.003	0.037	0.117	0.000
Higher education	0.139	0.113	0.288	0.030	0.073	0.003
Wealth index	-0.174	0.117	0.000	0.012	0.103	0.157
Subjective health						
very good	0.023	0.094	0.000	0.012	0.054	0.001
good	0.212	0.434	0.000	0.180	0.367	0.000
fair	0.619	0.442	0.000	0.643	0.528	0.000
bad	0.135	0.026	0.000	0.155	0.048	0.000
very bad	0.012	0.004	0.187	0.010	0.004	0.246
Glycated hemoglobin (HbA1c)	9.037	8.533	0.004	8.979	8.680	0.049
Hypertension (self-reported)	0.262	0.074	0.000	0.397	0.150	0.000
Blood pressure						
Systolic	136.688	130.506	0.000	136.070	122.835	0.000
Diastolic	84.677	82.063	0.003	84.495	79.689	0.000
Heart disease (self-reported)	0.035	0.007	0.004	0.050	0.024	0.021
BMI	28.868	28.311	0.135	30.640	29.778	0.032
Obese (BMI \geq 30)	0.338	0.311	0.440	0.469	0.431	0.225

Mean values.

Eq. 7. The results in panel D again only suggest a negative association of a one percentage point increase in HbA1c with female working hours for those with self-reported diabetes. For undiagnosed diabetes, we again found no effects.

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	-.055** (.026)	-.050** (.024)	-.308 (1.321)	-.323 (2.190)	-.026 (.066)	-.005 (.105)
Panel B: Diabetes (biomarker)						
Biomarker diabetes (HbA1c ≥ 6.5)	-.012 (.016)	-.032* (.018)	-.060 (.844)	1.067 (1.470)	-.008 (.045)	-.041 (.071)
Panel C: Interacting self-reported and biomarker diabetes						
Self-reported diabetes but tested negative (β_1)	-.049 (.059)	-.027 (.051)	1.547 (3.446)	7.417 (4.669)	0.250 (.205)	-.025 (.232)
Biomarker diabetes but not self-reported (HbA1c ≥ 6.5) (β_2)	0.005 (.018)	-.020 (.020)	0.174 (.960)	2.304 (1.639)	0.015 (.050)	-.049 (.078)
Self-reported diabetes and biomarker diabetes (β_3)	-.011 (.065)	-.015 (.059)	-2.255 (3.772)	-11.484** (5.423)	-.319 (.220)	0.059 (.265)
All self-reported ($\beta_1 + \beta_3$)	-.060** (.029)	-.042 (.031)	-.708 (1.571)	-4.067 (2.813)	-.069 (.084)	0.034 (.137)
Panel D: HbA1c levels						
Self-reported diabetes	-.067 (.072)	-.035 (.041)	1.471 (2.619)	4.974 (3.654)	0.157 (.119)	-.017 (.186)
HbA1c if ≥ 6.5	0.001 (.002)	-.003 (.002)	-.005 (.104)	0.235 (.193)	0.002 (.005)	-.005 (.008)
Self-reported diabetes \times HbA1c if ≥ 6.5	0.001 (.007)	0.000 (.005)	-.207 (.294)	-.852** (.424)	-.023 (.014)	0.005 (.022)
N	2785	3620	2302	1142	1803	882

Community level fixed effects. Robust standard errors in parentheses. All models control for states, urbanization, education, marital status, number of children, wealth, health insurance, 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Discussion

Diabetes is now one of the most common chronic diseases in low- and middle income countries, as well as high-income countries, 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, which showed alarming levels of undiagnosed diabetes.

Overall, the paper found evidence for adverse effects of self-reported diabetes on the probability of being employed, confirming earlier findings for Mexico that used cross-sectional information. But, these new results also suggested a comparatively larger impact of diabetes on female employment probabilities and that the main effects were driven by

345 those with a diabetes onset at a relatively later state, consisting most likely of people
346 with type 2 diabetes. Analyses of the long term impact indicated that the employment
347 probability fell gradually in the years following diagnosis. The results using non-linear
348 models were less clear, potentially due to reductions in statistical power, but suggested
349 that adverse effects became stronger with time since diagnosis. The linear effect contrasts
350 with estimates for the USA, where such an effect seemed to be absent, though their non-
351 linear analysis revealed falling employment probabilities after eleven to 15 years for females
352 and after two to five years for males (Minor 2013).

353 A relationship of diabetes with working hours or wages was mostly absent, except for
354 female wages that were reduced over time. Further, wages for men showed a positive
355 association with a diabetes diagnosis, in particular when using the between estimator.
356 This significant result may have arisen from individual selection due to higher paid men
357 being able to remain employed without experiencing wage reductions. They may also have
358 had access to better health care leading to better diabetes related health outcomes. Low
359 paid workers, on the other hand, may lack access to quality diabetes care, making it more
360 likely that they develop severe complications earlier and stop working (Flores-Hernández
361 et al. 2015). They are also more likely to be in informal employment and low skilled jobs,
362 making them easier replaceable with healthier workers.

363 Our results using the cross-sectional biomarker data suggested that those with undi-
364 agnosed diabetes were significantly healthier and younger. Consequently, diabetes based
365 on biomarkers was found to be less related to reduced employment, compared to self-
366 reported diabetes, due to the absence of any association between undiagnosed diabetes
367 and employment. These results are similar to those found for the USA, where no statis-
368 tically significant relationship between undiagnosed diabetes on employment was found,
369 while a significant effect of diagnosed diabetes was observed (Minor et al. 2016). Our
370 results further indicated that the difference in the employment effects of diagnosed and
371 undiagnosed diabetes was not mediated by current HbA1c levels, similar to findings for

Mexican-Americans in the USA, where employment outcomes were unrelated to higher HbA1c levels (H. S. Brown et al. 2011). Overall, it seemed that general health differences related to a longer diabetes duration and selection into the diagnosed population, for instance based on emerging diabetes related health problems, could be driving the adverse economic effects among those with a self-reported diagnosis.

Our study had several limitations. While the within-coefficient 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 play 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 et al. 2015), though they were carried out in high-income countries. For the duration analysis an additional limitation, imposed by the data, was that the year of diagnosis was only reported in the third wave.

Despite these limitations, our findings bear important implications. First, the impact of self-reported diabetes on labor outcomes in Mexico seems mostly limited to its effect on employment probabilities, though there is some indication that it could also reduce wages over time for women. Second, its effect on employment was much stronger for females. Potential explanations may be that lower working hours or wages for women make a dropout less costly. Further, women with diabetes have found to be in worse metabolic health compared to men when they cross the diabetes threshold (Peters et al. 2015), and hence may also have a higher risk to stop working due to diabetes complications. 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 subpopulations, and carry out a separate analysis whenever feasible. If this is not possible, study conclusions about the effect of self-reported diabetes should be limited

to this specific part of the population, in particular in environments where the share of undiagnosed diabetes is high, as is the case for most low- and middle income countries.

While we find no effect for undiagnosed diabetes in our cross section analysis, further inquiry over time is needed. The large proportion of previously undiagnosed cases 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 prematurely. Earlier diagnosis and ensuing effective treatment may lighten the health and economic burden. Further analysis is also needed to explain why the adverse economic effects are so large for women. Ultimately, prevention of diabetes is of high importance. Taxation of sugar sweetened beverages may be one promising way forward (Colchero et al. 2016), though their long-term effectiveness remains unclear. Given the established links between early life health and later life incidence of diabetes as well as other chronic diseases (Hanson et al. 2012; Li et al. 2010; Sotomayor 2013), investments in maternal and child health may be particularly attractive to address non-communicable and communicable diseases at the same time.

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517 Supplementary material

Table S1. Rules to deal with inconsistencies in diabetes self-reports over time.

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

518 Early versus late onset of diabetes

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

	Employment		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Early onset (within)	0.133 (0.176)	-0.206** (0.086)	14.712* (8.370)	-18.636* (9.668)	-0.523 (0.340)	0.388*** (0.057)
Late onset (within)	-0.059** (0.025)	-0.048* (0.025)	-1.008 (1.513)	-1.322 (2.553)	0.079 (0.067)	0.067 (0.163)
Early onset (between)	0.016 (0.037)	-0.052 (0.047)	1.483 (2.581)	-2.640 (4.034)	-0.102 (0.099)	0.286 (0.232)
Late onset (between)	-0.087*** (0.017)	-0.067*** (0.016)	-1.077 (0.895)	-0.869 (1.375)	0.121** (0.050)	-0.111* (0.066)
N	21388	27339	13828	7068	17616	9112

Robust standard errors in parentheses. All models control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey 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 (within)	0.030 (0.216)	−0.105 (0.074)	−0.225 (0.139)	−0.068 (0.047)	0.328** (0.161)	−0.027 (0.048)
Late onset (within)	−0.008 (0.029)	0.007 (0.018)	−0.002 (0.022)	−0.019** (0.009)	−0.053** (0.026)	−0.030 (0.019)
Early onset (between)	0.011 (0.055)	−0.050 (0.043)	−0.078*** (0.030)	−0.006 (0.007)	0.087 (0.056)	0.005 (0.029)
Late onset (between)	−0.037* (0.022)	−0.048*** (0.012)	−0.091*** (0.015)	−0.009*** (0.003)	0.039* (0.020)	−0.014 (0.011)
N	20719	26575	20719	26575	20719	26575

Robust standard errors in parentheses. All models control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey 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		Weekly work hours		Log hourly wages	
	Males	Females	Males	Females	Males	Females
Early onset (within)	−0.009 (0.017)	0.002 (0.013)				
Late onset (within)	−0.012** (0.005)	−0.007* (0.004)	0.086 (0.275)	0.308 (0.504)	−0.006 (0.013)	−0.059*** (0.022)
Early onset (between)	0.011*** (0.004)	−0.016*** (0.005)	−0.016 (0.012)	0.029 (0.051)	0.187 (0.333)	−0.401 (0.896)
Late onset (between)	−0.009*** (0.002)	−0.005*** (0.002)	−0.060 (0.117)	−0.144 (0.129)	0.011** (0.006)	−0.010 (0.009)
N	16308	22450	13592	7394	10778	5748

The within estimator for the effects of early onset diabetes on wages and working hours could not be estimates due to no within-variation for diabetes. Robust standard errors in parentheses. All models control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

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 control for states, urbanization, education, marital status, number of children, wealth, health insurance, age squared and survey year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	$\text{HbA1c} < 6.5\%$	$\text{HbA1c} \geq 6.5\%$	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