The Economics of Diabetes in Middle-Income-Countries

Till Seuring

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Abstract

Chapter 1

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

Chapter 2

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Chapter 3

The Impact of Diabetes on Labour Market Outcomes in Mexico: a Panel Data and Biomarker Analysis

Abstract

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

3.1 Introduction

Diabetes, and particularly its most common variant, type 2 diabetes, has increased worldwide and is expected to continue to rise over the next decades (**Risk2016**). It has become a problem for **MICs!** (**MICs!**) and high-income countrys (HICs) alike, with over two-thirds of people with diabetes living in the developing world (International Diabetes Federation, 2014). Mexicans and Mexican-Americans appear to be particularly affected by diabetes, also in comparison to other Latino populations living in the **USA!** (**USA!**) (**Schneiderman2014**). In Mexico itself, diabetes prevalence has been estimated to have grown from 6.7% in 1994 to 14.4% in 2006, including both diagnosed and undiagnosed cases (Barquera, Campos-Nonato, et al., 2013), and is expected to increase further over the next decades (**Meza2015**). Already now, diabetes is the number one cause of death in Mexico (Barquera, Campos-Nonato, et al., 2013).

The observed trend 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 have played a role (Williams et al., 2014). Recent evidence indicates that the onset of diabetes has been occurring at an ever earlier age in Mexico (Villalpando et al., 2010). With treatment as ineffective as it currently is —only a minority achieves adequate blood glucose control (Barquera, Campos-Nonato, et al., 2013)— the earlier onset will increase the likelihood of complications during the productive lifespan.

Diabetes is a term used to describe various conditions characterized by high blood glucose values, with the predominant disease being type 2 diabetes accounting for about 90 percent of all diabetes cases (Sicree et al., 2011). The elevated blood glucose levels that are a result of the body's inability to use insulin properly to maintain blood glucose at normal levels, can entail a range of adverse health effects for the individual concerned. However, via effective self-management of the disease much if not all of the complications can be avoided (**Lim2011**; **Gregg2012**). In the absence of effective self-management —or in the case of inadequate treatment— diabetes has been documented to lead to conditions such as heart disease and stroke, blindness, kidney problems, and nerve problems which together with impaired wound healing can lead to the loss of limbs (**Reynoso-Noveron2011**). These conditions can be seriously debilitating and may therefore reduce an individual's economic activity, including its productivity and labor market participation.

The effect of diabetes on labor market outcomes has been studied predominantly in

HICs —with the exception of a study on Mexico (Seuring et al., 2015) and one on China (Liu and Zhu, 2014) each. In the HIC studies diabetes has been found to be associated with reductions in employment probabilities as well as wages and labor supply (**Minor2010**; **Minor2015**; **Seuring2015a**; Brown, Pagán, et al., 2005; Brown, Perez, et al., 2011; Brown, 2014; Latif, 2009; Minor, 2013).

While these studies have provided useful evidence on the potential labor market effects of diabetes, many of the complexities of the relationship have not been comprehensively addressed in any given study. First of all, unobserved heterogeneity presents a challenge to estimate the relationship between diabetes and labor outcomes. Especially time-invariant unobserved individual characteristics, e.g. health endowments —often related to health during uteru, infant and child years, and to low household income or adverse health shocks during these early years— as well as risk preferences have been shown to adversely affect health in general and the propensity to develop type 2 diabetes more specifically (**VanEwijk2011**; **Sotomayor2013**; **Li2010b**). These and other unobserved personal characteristics (e.g. ability) may also affect employment probabilities, wages or working hours directly through their effects on contemporaneous productivity (**Currie2013**) and indirectly by limiting educational attainment and human capital accumulation (**Ayyagari2011a**). Further, only focusing on the overall effect of a self-reported diabetes diagnosis does not reveal when potential labor market penalties appear, given the dynamic aspect of diabetes and the potential differences in its effects over time. Additionally, apart from its health impact diabetes might also affect labor market outcomes through other channels. For instance, people aware of their condition may be less inclined to continue working if this interferes with their disease management or be suffering from psychological consequences (depression, anxiety) of becoming aware of the disease; they may also use the diagnosis as a justification for decreasing their labor supply, leading to a potential justification bias in the estimated effect of diabetes (**Kapteyn2009**). Importantly, for these reasons the labor market effects may also be distinct for people with self-reported versus those unaware of their condition, potentially leading to biased estimates if the analysis is solely based on self-reports.

The objective of this study is to provide new evidence on the impact of diabetes on labor outcomes, while improving upon previous work by paying close attention to the above challenges. We use three waves of panel data from Mexico covering the period 2002–2012, provided by the Mexican Family Life Survey (MxFLS). The MxFLS is particularly useful for the analysis of diabetes as it allows us to account for the above complexities in a more refined way than has been the case so far. Using individual level fixed effects (FE) analysis for the first time in this literature, we take account of time-invariant heterogeneity when assessing the impact of self-reported diabetes and self-reported diabetes duration on labor market outcomes.[1] Further, we add to the current literature in exploring the role of undiagnosed diabetes, using novel and rich biomarker data - an issue of considerable importance in light of the large prevalence of undiagnosed diabetes (see **Beagley2014**) that remained unaccounted for in most earlier studies which typically rely on self-reported information. Doing so sheds light on the issue of measurement error and the potentially differential effects of self-reported and undiagnosed diabetes.

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

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

3.2 Diabetes and labor outcomes – existing evidence

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

For the **USA!**, Brown, Pagán, et al. (2005) estimate the impact on employment in 1996–1997 in an elderly population of Mexican Americans living close to the Mexican border, using a bivariate probit model. The study finds diabetes to be endogenous for women but not for men. For the latter, the estimates show a significant adverse effect of 7 percentage points (p.p.). For women, the negative effect becomes insignificant when using instrumental variable (IV) estimation. In another study, again for a cross-sectional sample

[1] We are not aware of any other evidence on the effect on wages and working hours in a middle-income country (MIC).

of Mexican-Americans, Brown, Perez, et al. (2011) look at how diabetes management, inferred from measured glycated hemoglobin (HbA1c) levels, is associated with employment chances and wages. The authors detect a linear negative association between HbA1c levels and both employment chances and wages for men.

Two further studies also examine the impact of diabetes on employment and productivity for the **USA!**: **Minor2010** focuses on the effect of diabetes on female employment, earnings, working hours and lost work days in 2006, finding diabetes to be endogenous and its effect underestimated if exogeneity is assumed. In the IV estimates, diabetes has a significant negative effect on female employment as well as annual earnings but not on working hours. In a later study Minor (2013) investigates the relationship of diabetes duration and labor market outcomes using a cross-sectional analysis, providing evidence of a non-linear relationship, with employment probabilities declining shortly after diagnosis for men and after about 10 years for women; wages are not affected by duration. Finally, a recent study by **Minor2015** investigates the association of self-reported diabetes and undiagnosed diabetes with employment probabilities and working hours in an adult USA population, using cross-sectional data. This study indicates a reduction in the coefficient size of diabetes if undiagnosed diabetes cases are included in the diabetes indicator instead of only self-reported diabetes. Further, they find that there is no association of undiagnosed diabetes with employment probabilities itself. However, the results of the study, particularly those for undiagnosed diabetes, are based on a very small number of cases, warranting further investigation.

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

To the best of our knowledge only two studies exist for non-HICs. Liu and Zhu (2014) investigate the effect of a diabetes diagnosis on labor income in China, exploiting a natural experiment to identify causality and find a significant reduction in income for those with a recent diagnosis. An earlier study for Mexico explored the effect of self-reported diabetes on the probability of employment using only cross-sectional data from the 2005 wave of the MxFLS, and found a significant ($p<0.01$) reduction in employment chances for males by about 10 p.p. and for females by about 4.5 p.p. ($p<0.1$), using parental diabetes as an IV (Seuring et al., 2015). The scarcity of evidence for **LMICs!** (**LMICs!**) is also documented in a recent systematic review of the economic cost of diabetes (**Seuring2015a**).

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

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

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

3. The use of self-reported diabetes can introduce non-classical measurement error due to systematic misreporting which has been shown to cause estimates of economic impacts to be potentially biased and overstated (**Cawley2015**; **ONeill2013**; **Perks2015**).

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

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

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

3.3 Data

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

Because the response to this question may well suffer from measurement error due to recall bias, we investigate and try to increase the consistency of the self-reported diabetes variable, using disease information from earlier and ensuing waves to infer on the current, missing or inconsistent, diabetes status (see Appendix .1 for further details on our correction procedures). A further, and no less important, source of measurement error is the omission of those with undiagnosed diabetes. In order to investigate how this may affect estimates of the labor market impact of diabetes we use information from a subsample of the 2009-2012 wave containing over 6000 respondents (everybody aged 45+ and a random subsample of those aged 15–44 (**Crimmins2015**)) that have biometrically measured blood glucose values, allowing for the identification of those with undiagnosed diabetes. Throughout our analysis the samples we use are restricted to the working age population (15–64). To prevent pregnant women from biasing our results due to the increased diabetes risk during pregnancy and its effects on female employment status, we have dropped all observations of women reporting to be pregnant at the time of the survey (N=764). We further exclude everybody currently in school.

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

[3]Employment status is defined as having worked or carried out an activity that helped with the household expenses the last week and working for at least four hours per week. This explicitly includes those employed informally, for instance people working in a family business.

[4]Hourly wage was calculated by adding up the reported monthly income from the first and second job (if any) and dividing it by the average number of weeks per month. This gave us the average earnings per week which were then divided by the weekly working hours to arrive at an hourly wage estimate. Labor income was either reported as the total amount for the whole month or more detailed containing information on the monthly wage, income from piecework, tips, extra hours, meals, housing, transport,

Table 3.1: Descriptive statistics for panel and biomarker sample.

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

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

data of all three waves (Table 3.1), diabetes was self-reported by 5% of men and 6% of women, respectively. This is consistent with other prevalence estimates of self-reported diabetes for this time period in Mexico.[5] About half of the respondents in the sample live in rural areas. Looking at our outcome variables, 86% of men report some form of employment compared to 37% of women. Interestingly, men do not report considerably higher hourly wages than women but work more hours per week. Also, men are working more often in agricultural jobs while women are more likely to be self-employed or in non-agricultural wage employment. Women also have lower educational attainment on average.

Turning to the biomarker subsample of the third wave (2009-2012), respondents are somewhat older on average than in the pooled sample, as it includes everybody above the age of 44 but only a random subsample of those aged 44 or below (**Crimmins2015**). Also, self-reported diabetes is higher than in the pooled sample[6]. Regarding the other control and outcome variables, the sample is fairly similar to the pooled sample. Remarkably, a relatively large share of people have an HbA1c indicative of diabetes, defined by the World Health Organization (WHO) as levels above or equal 6.5% (World Health Organization, 2011)[7]: 18% of males and females are unaware of their diabetes. This suggests that relying on self-reported diabetes as a measure for diabetes in Mexico might considerably understate the true extent of diabetes, potentially leading to biased estimates of its economic impact.

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medical benefits and other earnings. Over 80% of respondents reported the total amount instead of a detailed amount. Respondents were also asked for their annual income and we used that information to arrive at an hourly wage if information for monthly labor income was missing. Finally, we adjusted the calculated wage for inflation from the year of the interview up to 2013 and took the log of those values. Due to a considerable number of missing or zero income reports the sample used for the wage estimation is smaller than the sample for working hours. Working hours were calculated summing up the self-reported working hours of the first and —if applicable— the second job.

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

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

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

3.4 Estimation strategy

Strauss1998 provide a useful framework to think about the relationship between health and labor outcomes:

$$L = L(H, pc, w(H; S, A, B, I, \alpha, e_w), S, A, B, V, \xi) \tag{3.1}$$

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

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

There are several ways diabetes may affect H. First of all, diabetes can deteriorate health if it remains untreated, with the adverse effects potentially increasing over time. Second, a diagnosis of diabetes and ensuing treatment may lead to better health compared to the undiagnosed state. However, compared to healthy people even those receiving treatment for their diabetes may still have worse health outcomes. Third, there is also evidence that the diagnosis itself may affect one's own health perception and could lead to worse self-perceived health (**Thoolen2006**). We therefore expect diabetes to adversely affect health and consequently labor market outcomes.

When estimating Eq. 3.1 empirically with observational data, unobserved heterogeneity may bias the results. As mentioned in section 3.1 unobserved factors captured in α such as early childhood investments, innate ability and risk preference could affect wages as well as the probability to develop diabetes. Further, changes in lifestyle due to changes in wages or employment status may also affect the probability to develop diabetes through changes in diet and physical activity. Finally, measurement error e_w may be an important issue due to the large undiagnosed population with diabetes, particularly if being diagnosed is related to employment or wages via better access to healthcare through employment benefits and higher income.

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

3.4.1 Panel data on self-reported diabetes

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

We estimate the following model:

$$Y_{it} = \beta_0 + \beta_1 Diabetes_{it} + \beta_2 X_{it} + c_i + \gamma_t + u_{it}. \tag{3.2}$$

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

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

The control variables in both FE specifications include dummy variables to capture the effects of the living environment, of living in a small, medium or large city with rural as the reference category, and state dummies. We also include a marital status dummy and the number of children residing in the household below the age of 6 to control for the impact of marriage and children on labor market outcomes and the effect of childbearing

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

[9] Results are available on request.

[10] We are not able to distinguish between type 1 diabetes and type 2 diabetes using this data. Other studies that tried to assess the effect of type 1 diabetes on labor market outcomes have found no association (**Minor2010**; **Minor2015**). Including type 1 diabetes therefore likely attenuates any adverse relationship we may find.

and related gestational diabetes on the probability of developing type 2 diabetes (Bellamy et al., 2009). To account for the effect of changes in household wealth on diabetes and employment probabilities, we use standard principal component analysis of multiple indicators of household assets and housing conditions to create an indicator for household wealth[11] (Filmer and Pritchett, 2001). Finally, a quadratic age term and calendar year dummies are included to capture the non-linear effect of age and any trends over time, respectively.

Before moving on, it bears emphasizing that despite our efforts to reduce any bias in our estimates, the estimated coefficients do not reflect true causal effects since time-variant unobserved heterogeneity may still bias the estimates. With respect to employment status, one potential issue would be that job loss affects lifestyle choices that increase the probability to develop diabetes, which could then in turn negatively affect labor market outcomes. So far, no strong adverse effects of job loss as a result of diabetes self-reports have been reported in the literature (**Bergemann2011**; **Schaller2015**), but this has so far only been researched in a high-income country context. Another example relates to stress at work, which has been linked to the development of type 2 diabetes (**Heraclides2012**; **Eriksson2013**). However, while stress levels may change over time, a person's coping mechanisms to deal with stress are likely time-invariant (**Schneiderman2005**). While we cannot exclude the role of these time variant unobserved factors, it seems that the role of time-invariant variables, e.g. genetic predisposition and relatively stable personality traits, is predominant. The applied FE approach should then limit the bias resulting from these time-invariant confounding factors.

3.4.2 Self-reported diabetes duration

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

$$Y_{it} = \beta_0 + \beta_1 Dyears_{it} + \beta_2 X_{it} + c_i + u_{it}, \tag{3.3}$$

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

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

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

$$Y_{it} = \delta_0 + g(Dyears_{it}) + \delta_2 X_{it} + c_i + u_{it}. \tag{3.4}$$

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 $n = 1, 2, \ldots, N$. We choose three nodes that —based on visual inspection (see Figures 3.1, 3.2 and 3.3 in Section 3.5.2)— best captured any possible non-linearity in the relationship between diabetes duration and labor outcomes. These are located at 4, 11 and 20 years after diagnosis. The first four years should capture any immediate effects of the diagnosis, the years five to eleven should capture any effects of adaptation to the disease. After 11 years it is conceivable that many of the debilitating complications of diabetes would appear that could deteriorate health and lead to adverse effects on labor market outcomes. The coefficient δ_n captures the effect of diabetes for the n-th interval. The effects are linear if $\delta_1 = \delta_2 =, \ldots, = \delta_n$.

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

One caveat of using FE is that, when year dummies are included, any variable that varies by one unit in each time period, is not separately identified (**Wooldridge2012**). Because this is also the case for diabetes duration, in Eq. (3.3) and Eq. (3.4), identification of this variable relies on the presence of people without diabetes in the sample, for which diabetes duration does not increase at the same rate as time.[13] As a further robustness check, we also estimate two models that only use between-individuals variation, i.e. a linear probability model (LPM) that uses only data from the third wave, the only wave where year of diagnosis was originally reported, and a pooled LPM that used data from all three waves.[14]

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

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

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

3.4.3 Cross-section: biomarker and self-reported data

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

1. Systematic overreporting of diabetes: people without diabetes may report a diabetes diagnosis, unintentionally —for instance due to misdiagnosis, either from a health professional or because of self-diagnosis, or intentionally— for instance with a view to justifying some other adverse event or status in their life (e.g. being unemployed).

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

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

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

The health information received at a diabetes diagnosis may also have an effect in itself. It may for instance affect an individual's psychology which in turn may influence economic behavior. Two studies found a diabetes diagnosis and subsequent treatment to increase

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

the odds of psychological problems, including depression and anxiety (**Thoolen2006**; **Paddison2011**), while similar results have not been found for people with undiagnosed diabetes (**Nouwen2011**). Looking at behavioral change, health information has been shown to affect behavior after the diagnosis of not only diabetes (**Slade2012**) but also of other chronic diseases (see **Baird2014**; **Gong2015**; **Thornton2008**; **Zhao2013a**). However, little is known about the effects of health information on labor market outcomes. For diabetes, only Liu and Zhu (2014) investigate the effect of receiving a diabetes diagnosis on labor income in Chinese employees. This study finds a reduction in labor income which was attributed to the psychological effects of the diagnosis.[16]

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

Our analysis of the biomarker sample consists of three steps. We first estimate Eq. 3.5 to assess the association of self reported diabetes with labor outcomes, as before, but this time for the biomarker sample only, using the following specification:

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 X_i + c_i + u_i \tag{3.5}$$

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

$$Y_i = \beta_0 + \beta_1 Dbio_i + \beta_2 X_i + c_i + u_i \tag{3.6}$$

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

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

[16] In a very different context **Dillon2014**, using a randomized intervention, find that the news stemming from diagnosis of malaria affects productivity and income, but not labor supply among sugar cane cutters in Nigeria.

$$Y_i = \beta_0 + \beta_1 Dsr_i + \beta_2 Dbio_i + \beta_3 X_i + v_i + u_i. \tag{3.7}$$

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

3.5 Results

3.5.1 Incidence of self-reported diabetes

Table 3.2 presents the estimation results of the FE model using Eq. 3.2, which indicate significant and substantial reductions in the probability of employment for men and women with self-reported diabetes. The effects are surprisingly similar across both sexes, showing a reduction in employment probabilities of over 5 p.p..

Table 3.2: Self-reported diabetes and labor market outcomes.

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

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

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

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

Table 3.3: Effect of self-reported diabetes on wages and working hours, by type of work.

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

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

The results in Table 3.3 show that while male agricultural workers have lower wages in general, the relationship with diabetes does not depend on the type of work, as none of the interaction terms show up as significant. In the working hours regression one interaction term is significant, suggesting that those with self-reported diabetes working in agriculture supply 5 hours less relative to non-agricultural workers and employees. However, because we have more than two work types we cannot draw conclusions solely on the basis of the t-statistic. We therefore perform a Wald test for the overall significance of the interaction term which does not reject the null of no interaction effects ($p = .15$), indicating that the effect of diabetes on working hours does not vary significantly by type of work.

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

To explore whether diabetes affects the selection into certain types of work we estimate FE models of the probability of being in non-agricultural wage employment, agricultural employment or self-employment using three dummy variables indicating the respective type of work as the left hand side variables. The results in Table 3.4 indicate a negative association with self-employment, though the estimates are quite imprecise. For women, those who self-report diabetes are less likely to work in agriculture and potentially self-employment. This may suggest that having diabetes drives people out of self-employment and agricultural jobs, for instance because these jobs are physically more demanding and possibly also because they provide less protection in terms of insurance and employment duration. We also estimated a pooled multinomial logit model augmented with the within-between approach (**Bell2015**), based on the work of **Mundlak1978**, which allows interpreting the coefficients of all time-varying variables as within-effects by including individual means of all time-varying covariates[18]. The results indicate a very similar pattern both in size and significance (results available on request).[19]

Table 3.4: Relationship between self-reported diabetes and selection into types of work.

	Males			Females		
	(1) Non-agric.	(2) Agric.	(3) Self-employed	(4) Non-agric.	(5) Agric.	(6) Self-employed
Self-reported diabetes	$-.006$	$-.008$	$-.043$	$-.001$	$-.022^{**}$	$-.029$
	(.029)	(.022)	(.026)	(.018)	(.009)	(.018)
N	20719	20719	20719	26577	26577	26577

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

[18]Several other studies in economics have used this approach recently, e.g., **Geishecker2011**; **Wunder2014**; **Boll2016**

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

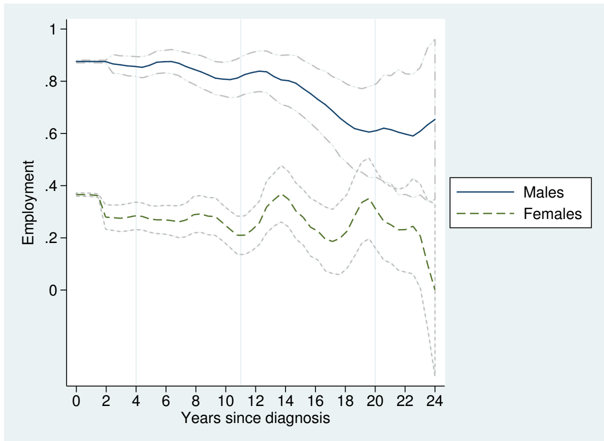
3.5.2 Duration of self-reported diabetes

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

To obtain an initial idea of the relationship between our outcome variables and diabetes duration we use a non-parametric kernel-weighted local polynomial regression. As Figure 3.1 shows, the relationship between diabetes duration and the probability of employment for men shows a more or less steady decline that becomes more pronounced as time progresses. For women, a first drop-off occurs right after diagnosis; thereafter no consistent pattern is observed.[20] A similar analysis for wages shows somewhat more erratic relationships, although there seems to be a long term negative trend for women but not for men (see figures 3.2 and 3.3). A similar negative trend can be observed for working hours for women, but not for men.

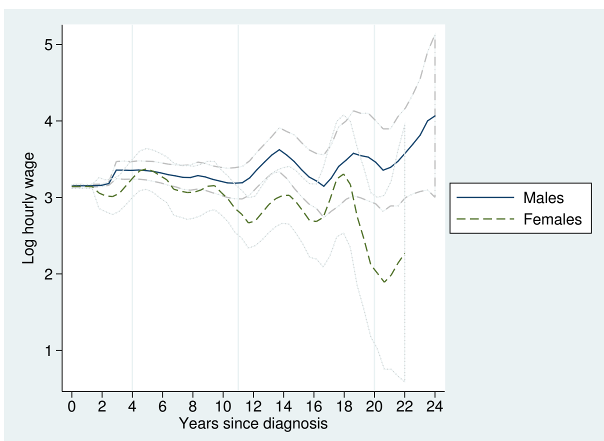
[20]Since long run estimations suffer from large standard errors —as the sample size is strongly reduced— this limits its interpretation and we therefore truncate the graphs at a disease duration of 24 years.

Figure 3.1: Kernel-weighted local polynomial regression of employment status on diabetes duration.



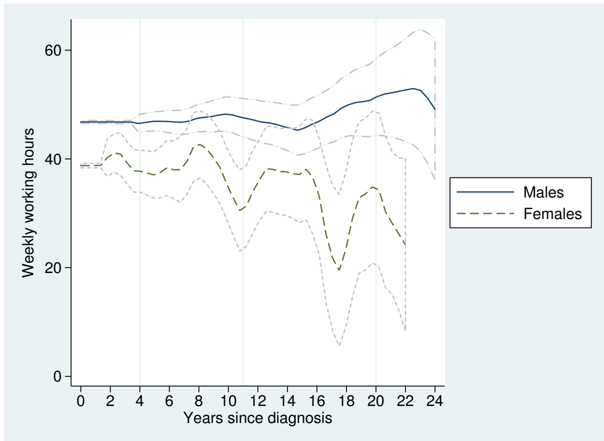
The dotted lines around the main line show 95% confidence intervals.

Figure 3.2: Kernel-weighted local polynomial regression of log hourly wages on diabetes duration.



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

Figure 3.3: Kernel-weighted local polynomial regression of working hours on diabetes duration.



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

Table 3.5 presents the results of the linear and non-linear duration models (for which we created the following splines to capture the immediate, intermediate and long-term relationships:0–4, 5–11, 12–19 and 20+), starting with the results of the cross-sectional LPM, followed by the pooled LPM and then the FE model as specified in Eq. (3.3) and Eq. (3.4).

For employment probabilities the results indicate a yearly reduction in male employment probability throughout. For women the coefficient shows a reduction of up to almost 1 p.p. per year, though the association is not as strong in the FE model. The coefficients in the spline models provide some evidence for an immediate effect of diabetes, which then levels off for some time after which it becomes stronger again. Nonetheless, for males and particularly females, the coefficients are quite imprecisely measured.

Turning to wages, the FE model indicates a reduction in female wages of about 7% per year with diabetes. For men we find no consistent effect. The results of the non-linear specification indicate that there may be a reduction in wages 5–11 years after the initial diagnosis. We also find associations for women with more than 20 years of diabetes, but these estimates may be spurious due to the considerably reduced number of observations in this group.[21]. There appears to be no consistent relationship between working hours

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

Table 3.5: Relationship between self-reported years since diagnosis and labor market outcomes using continuous duration and duration splines.

	Males			Females		
	(1) OLS (wave 3)	(2) Pooled OLS	(3) FE	(4) OLS (wave 3)	(5) Pooled OLS	(6) FE
			Employment probabilities			
Panel A:						
Diabetes duration (linear)	$-.008^{***}$	$-.007^{***}$	$-.017^{***}$	$-.005^{***}$	$-.004^{***}$	$-.009^{*}$
	(.002)	(.002)	(.006)	(.002)	(.001)	(.005)
Panel B:						
Diabetes duration (splines)						
0–4	−.007	−.007	$-.026^{*}$	−.010	$-.015^{**}$	−.017
	(.007)	(.006)	(.014)	(.007)	(.006)	(.016)
5–11	0.000	−.003	−.003	−.004	0.004	−.003
	(.009)	(.006)	(.009)	(.008)	(.006)	(.008)
12–20	$-.030^{**}$	$-.017^{*}$	$-.029^{*}$	0.005	−.004	−.014
	(.012)	(.010)	(.016)	(.008)	(.006)	(.011)
> 20	0.011	0.007	$-.046^{*}$	$-.010^{*}$	−.003	−.015
	(.016)	(.014)	(.028)	(.006)	(.003)	(.018)
N	8217	16292	16292	10467	22407	22407
			Log hourly wage			
Panel A:						
Diabetes duration (linear)	0.001	0.010^{**}	−.019	$-.014^{*}$	−.009	$-.073^{**}$
	(.006)	(.005)	(.018)	(.008)	(.008)	(.029)
Panel B:						
Diabetes duration (splines)						
0–4	0.034^{*}	0.046^{***}	0.033	0.027	0.030	0.015
	(.017)	(.016)	(.055)	(.031)	(.026)	(.138)
5–11	$-.041^{*}$	$-.037^{**}$	$-.055^{*}$	−.039	−.034	$-.101^{*}$
	(.021)	(.018)	(.033)	(.030)	(.024)	(.056)
12–20	0.015	0.044	0.062	−.032	$-.071^{*}$	−.051
	(.033)	(.029)	(.056)	(.042)	(.039)	(.047)
> 20	0.053	0.014	−.111	−.007	0.041^{***}	$-.204^{***}$
	(.054)	(.040)	(.104)	(.028)	(.015)	(.053)
N	5509	10767	10767	2874	5741	5741
			Weekly working hours			
Panel A:						
Diabetes duration (linear)	0.069	0.048	0.181	−.020	−.124	0.208
	(.124)	(.102)	(.330)	(.187)	(.127)	(.652)
Panel B:						
Diabetes duration (splines)						
0–4	−.033	−.233	0.709	0.739	0.470	2.014
	(.421)	(.325)	(.938)	(.645)	(.586)	(2.947)
5–11	0.269	0.338	−.218	−.410	−.479	−.508
	(.539)	(.399)	(.568)	(.728)	(.553)	(1.020)
12–20	0.209	0.137	0.698	−.164	−.051	−.402
	(.730)	(.538)	(.945)	(.995)	(.700)	(1.207)
> 20	−1.300	−.768	0.039	−.499	−.418	8.117^{***}
	(.944)	(.930)	(2.184)	(.930)	(.305)	(1.612)
N	6807	13579	13579	3591	7383	7383

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

and time since being diagnosed with diabetes.

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

3.5.3 Cross-sectional biomarker analysis

In this section we gain additional insights from using the biomarker data collected in the third wave of the MxFLS. As noted in section 3.3, these data enable us to identify respondents with HbA1c levels equal to or above the internationally recognized diabetes threshold of 6.5%. This will allow the investigation of the direction of bias introduced when relying on self-reported diabetes only and when it is not possible to identify those unaware as well.

We first present a cross tabulation of self-reported diabetes and the results of the biomarker analysis (Table 3.6). The table indicates that 27% of the sample have HbA1c levels indicative of diabetes and 81% of those self-reporting a diabetes diagnosis also have HbA1c levels equal to or above the diabetes threshold. Overall, of the people with diabetes according to biomarker analysis, 32% self-report a diagnosis, while 68% do not.

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

Table 3.6: Number of observations with diabetes (HbA1c $\geq$ 6.5%) and self-reported diabetes.

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

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

To further investigate the relationship of self-reported and biomarker tested diabetes, we estimate the models presented in section 3.4.3. The results in columns 1 and 2 of Table 3.7 show that the earlier results are robust for the biomarker sample. The coefficients in column 3 and 4 indicate that the associations with employment probabilities are much weaker when using diabetes defined by the biomarker instead of self-reported diabetes.[23] In columns 5 and 6, obtained from estimating Eq. 3.7, the coefficient for the biomarker diabetes population $Dbio_i$ now reflects the effect of undiagnosed diabetes, as the regression includes a control for self-reported diabetes, revealing that undiagnosed diabetes is not associated with any of the labor outcomes. The coefficient for self-reported diabetes is marginally bigger in size for men and somewhat smaller for women compared to column 1 and 2, respectively. However, these differences are not statistically significant (p>0.1) using a Z-test, suggesting that not accounting for undiagnosed diabetes will likely leave the estimates of self-reported diabetes unbiased.

As discussed earlier, differences in effects between self-reported diabetes and those undiagnosed are likely to stem from selection into the diagnosed population, for instance those in worse health or higher HbA1c levels are more likely to go to the doctor and

[23]We also created a dummy variable that additionally to measured diabetes accounted for those with a self-reported diabetes diagnosis but biomaker levels below the diabetes threshold. This allowed us to investigate the effect for the entire diabetes population. The coefficients and their statistical significance are only marginally different to those presented in columns 3 and 4 of Table 3.7, which is why we do not present them here.

Table 3.7: Biomarker results

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

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

be diagnosed as well as to lose their job because of their diabetes. To further explore this, we first estimate models additionally controlling for self-reported health status to capture differences in subjective individual health. Secondly, we investigate in how far differences in measured HbA1c, as a proxy for diabetes severity, may explain differences in employment effects of self-reported and undiagnosed diabetes. To this end we estimate Eq. 3.7 additionally controlling for HbA1c levels.

When additionally controlling for subjective health status, we find that for men and women the difference between self-reported diabetes and undiagnosed diabetes is reduced due to a smaller coefficient for self-reported diabetes (Table 3.8, Panel A). Especially for females, the point estimates for self-reported diabetes and undiagnosed diabetes are now virtually the same size, suggesting that differences can be almost exclusively explained by self-reported health. For men, factors not captured by self-reported health may still

Table 3.8: Self-reported diabetes, biomarkers, diabetes severity and self-reported health and their association with labor market outcomes

	Employment		Log hourly wages		Weekly working hours	
	(1) Males	(2) Females	(3) Males	(4) Females	(5) Males	(6) Females
Panel A (self-reported health)						
Self-reported diabetes	−.036	−.023	0.002	0.060	0.123	−2.191
	(.026)	(.027)	(.079)	(.121)	(1.433)	(2.386)
Hba1c ≥ 6.5%	0.003	−.023	−.004	−.051	−.066	1.829
	(.017)	(.019)	(.049)	(.075)	(.926)	(1.569)
Self-reported health status						
good	0.023	0.057*	0.061	−.115	−1.131	3.521
	(.025)	(.034)	(.074)	(.124)	(1.376)	(2.499)
fair	−.007	0.006	0.025	−.157	−1.606	4.646*
	(.026)	(.034)	(.076)	(.128)	(1.424)	(2.607)
bad	−.127***	−.024	−.016	−.371*	−6.190**	6.918*
	(.043)	(.046)	(.135)	(.189)	(2.521)	(3.858)
very bad	−.165	0.117	−.331	0.316	−1.869	−17.400*
	(.110)	(.116)	(.300)	(.439)	(6.433)	(9.005)
N	2785	3621	1803	883	2302	1143
Panel B (HbA1c levels)						
Self-reported diabetes	−.056*	−.027	−.007	0.002	0.076	−1.440
	(.031)	(.025)	(.068)	(.114)	(1.362)	(2.382)
HbA1c ≥ 6.5%	−.005	−.005	−.010	−.019	1.032	1.887
	(.023)	(.026)	(.060)	(.099)	(1.279)	(2.490)
HbA1c	0.003	−.006	0.001	−.012	−.364	−.122
	(.005)	(.006)	(.013)	(.021)	(.279)	(.514)
N	2785	3623	1803	884	2302	1144

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

play a role. Additionally accounting for measures of overweight and obesity, self-reported hypertension, heart disease and depression does not further affect the interpretation of the diabetes coefficient (results available on request).

Turning to Panel B, we do not find an indication that differences in HbA1c levels are driving the different employment effects of diabetes for the aware and unaware. We therefore conclude that current diabetes severity is likely not associated with any labor outcome and does not explain the difference in effects between diagnosed and undiagnosed diabetes.

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

3.6 Conclusion

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

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

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

The first part of our results confirms a considerable gap in employment probabilities for both men and women reporting a diabetes diagnosis, compared to those that do not report the condition. We also find some evidence that diabetes is more likely to reduce the probability of employment in the agricultural and self-employment sector, characterized predominantly by informal arrangements, compared to the rest of the workforce. Those who remain employed do not suffer any wage or labor supply effects, possibly because they are still relatively healthy or are able to resort to a type of work that does not entail their diabetes status limiting their work-related performance. More research will be needed to confirm and further investigate this finding as well as its interpretation.

Regarding the heterogeneity in the effects of diabetes over time, our results indicate an adverse impact of self-reported diabetes on employment chances, with the impact growing in magnitude especially after the first 10 years post-diagnosis. This is plausible in that as time lived with diabetes evolves, complications associated with diabetes tend to become more frequent and more severe (**Adler2003**). Looking at wages as our labor market outcome, we uncover some adverse effects for females, indicating a sizable reduction with time since diagnosis. These findings may bode ill for countries were diabetes has started appearing at an increasingly younger age, causing people to live with the disease for larger parts of their productive lifespan, possibly exacerbating the economic effects of reduced employment due to diabetes (**Hu2011**; Villalpando et al., 2010).

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

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

Further, the results of the biomarker analysis also reveal that the coefficient of self-reported diabetes is not strongly affected when accounting for biomarker diagnosed diabetes, suggesting that using self-reported diabetes still provides largely unbiased estimates. The latter estimates should then of course only be used to draw conclusions about the effect of self-reported diabetes, not of diabetes overall. In the case of Mexico, given that more than 7% of the Mexican population have been diagnosed with diabetes, the identified reduction in employment probabilities still amounts to a significant overall economic burden being associated with (diagnosed) diabetes.

Our results add further weight to the case for reducing the incidence and progression of diabetes. On top of the well-documented health benefits, it appears there are considerable potential gains to be had in terms of increasing the productive lifespan of people. This is of particular importance in **LMICs!**, where parental health shocks, related job loss and increasing health expenditures can have repercussions across the entire household. Other family members, including children, may be forced to increase their labor supply and to reduce non-health expenditures in order to prevent deterioration of the household's economic situation. This can lead to forgone investments into child education, showcasing the potential for adverse long-term effects of health shocks due to diabetes (**Bratti2014**). Moreover, the large proportion of undiagnosed people indicates that diagnosis —at least in Mexico— happens too late or not at all, thereby significantly reducing the possibility to prevent complications via appropriate treatment and self-management, which has repercussions by increasing the risk of severe complications appearing early. Hence, much of the health and economic burden may be prevented by earlier diagnosis and, given the generally limited success in achieving good control in Mexico, better treatment of those already diagnosed with diabetes. Ultimately of course, there will be a need to invest in the prevention of diabetes cases in the first place. Taxation of sugar sweetened beverages may be one promising way forward (**Colchero2016**), though the long-term effects in terms of diabetes prevention remain to be demonstrated.

Appendix

.1 Strategies to deal with inconsistent self-reporting over time

Reporting error is likely to pose a considerable challenge in the use of self-reported data. Fortunately, the MxFLS data provides several possibilities to assess the amount of misreporting and to attempt to limit before estimating the labor market effects of diabetes. In what follows we describe our approach of dealing with inconsistencies in self-reported diabetes over time.

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

We also find inconsistencies in the diabetes self-reports over the three waves of the MxFLS data, with between 10–20% of those reporting diabetes in one wave not doing so in one of the subsequent waves. In order to reduce the amount of inconsistencies, we were interested in the validity of diabetes self-reports. While we could not find a study assessing the validity of self-reported diabetes in Mexico, a study from China has shown that specificity of self-reported diabetes, i.e. those who self-report a diabetes diagnosis actually have diabetes, was very high (>98% for China), while sensitivity, i.e. how many people with diabetes, diagnosed or undiagnosed, actually self-report the disease, was low (40% for China) (**Yuan2015**). This indicates that people who report a diabetes diagnosis are likely to indeed have the condition while many of those not reporting a diabetes diagnosis are unaware of their diabetes.

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

We used this information to infer the "true" diabetes status for those with inconsistent reports. For those with two waves, we assumed that if a diabetes diagnosis had been reported in a prior wave they also had diabetes in the ensuing wave, even if then it was not reported. For people where we had data from all three waves, we used that additional information to make a decision on how to deal with inconsistencies using the rules outlined in Table 9

Table 9: Inconsistencies in diabetes self-report in MxFLS.

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

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

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