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

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**Abstract**

There is limited evidence on the labour 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. Comple-mentary biomarker information for a cross section indicates that a large diabetes population is unaware of the disease. The results indicate that the adverse eﬀects found for self-reported diabetes do 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.

* **Introduction**

Diabetes, and particularly its most common variant, type 2 diabetes, has increased world-wide and is expected to continue to rise over the next decades (NCD Risk Factor Collabora-tion, 2016). It has become a problem for middle-income countrys (MICs) and high-income countries (HICs) alike, with over two-thirds of people with diabetes living in the develop-ing world (International Diabetes Federation, 2014). Mexicans and Mexican-Americans appear to be particularly aﬀected by diabetes, also in comparison to other Latino popu-lations living in the USA (Schneiderman, Llabre, et al., 2014). In Mexico itself, diabetes prevalence has been estimated to have grown from 6.7% in 1994 to 14.4% in 2006, includ-ing both diagnosed and undiagnosed cases (Barquera, Campos-Nonato, et al., 2013), and is expected to increase further over the next decades (Meza et al., 2015). Already now,

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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., 2013). 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% 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 (Gregg et al., 2012; Lim et al., 2011). 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-Noverón et al., 2011). These conditions can be seriously debilitating and may therefore reduce an individual’s economic activity, including its productivity and labour market participation.

The eﬀect of diabetes on labour market outcomes has been studied predominantly in HICs—with the exception of a study on Mexico (Seuring, Goryakin, 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 labour supply (Brown, Pagán, et al., 2005; Brown, Perez, et al., 2011; Brown, 2014; Latif, 2009; Minor, 2011, 2013; Minor and MacEwan, 2016; Seuring, Archangelidi, et al., 2015).

While these studies have provided useful evidence on the potential labour 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 labour market 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 (Ewijk, 2011; Li et al., 2010; Sotomayor, 2013). 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 (Currie and Vogl, 2013) and indirectly by limiting educational attainment and human capital accumulation (Ayyagari et al., 2011). Further, only focusing on the overall eﬀect of a self-reported diabetes diagnosis does not reveal when potential labour 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 labour

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 labour supply, leading to a potential justification bias in the estimated eﬀect of diabetes (Kapteyn et al., 2009). Importantly, for these reasons the labour 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 labour market 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 pe-riod 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 com-plexities 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 dia-betes duration on labour 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 Beagley et al. (2014)) that remained unaccounted for in most earlier studies which typi-cally 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 em-ployment penalty, while biometrically measured diabetes does not. Overall, undiagnosed diabetes does not appear to aﬀect any of the labour market outcomes examined here, suggesting that adverse eﬀects mainly occur to those self-reporting a diagnosis. We ar-gue 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.

* **Diabetes and labour market outcomes—existing ev-idence**

Several studies have investigated the eﬀects of diabetes on labour 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,

1We are not aware of any other evidence on the eﬀect on wages and working hours in a MIC.

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. For women, the negative eﬀect becomes insignificant when using instrumental variable (IV) estimation. In another study, again for a cross-sectional sample of Mexican-Americans, Brown, Perez, et al. (2011) look at how diabetes management, inferred from measured glycated hemoglobin (HbA1c) levels, is associated with employment probabilities and wages. The authors detect a linear negative association between HbA1c levels and both employment probabilities and wages for men.

Two further studies also examine the impact of diabetes on employment and produc-tivity for the USA: Minor (2011) 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 du-ration and labour 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 Minor and MacEwan (2016) 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 associa-tion 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) analyse the eﬀects of diabetes on labour force participation using a multivariate endogenous probit model. Their results demonstrate reduced labour 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 labour income in China, exploiting a natural experiment to identify causality, finding 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 probabilities for males by about 10 percentage points and for females by about 4.5 percentage points (p<0.1), using parental diabetes as an IV (Seuring, Goryakin, et al., 2015). The scarcity of evidence for low- and middle-income countrys (LMICs) is also documented in a recent systematic review of the economic cost of diabetes (Seuring, Archangelidi, et al., 2015).

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 dia-betes. 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 labour market outcomes directly. This traditional identification strategy also abstracts from intrahousehold or intergenerational labour supply eﬀects (Seuring, Goryakin, 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 (Cawley et al., 2015; O’Neill and Sweetman, 2013; Perks, 2015).
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.

* **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,

2It 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 labour supply to compensate for lost income.

missing or inconsistent, diabetes status (see page in the Appendix 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 labour 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 (Crimmins et al., 2015)) 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: employment3, hourly wage and weekly working hours4. For the pooled data of all three waves (Table 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 (Crimmins et al., 2015). Also, self-reported diabetes is higher than in the pooled sample6. Regarding the

3Employment 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. We also tested if changing the definition of being employed to having worked at least ten hours per week. This only led to marginal changes in the coeﬃcients and standard errors, not aﬀecting the interpretation of the results.

4Hourly 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. labour 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, 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 labour 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.

5Barquera, 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.

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

Table 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 |  |  |
| Non-agricultural worker | (0.39) | (0.45) | (0.41) | | (0.47) |  |  |
|  |  |  |  |  |  |  |
| or employee | 0.59 | 0.68 | 0.53 | | 0.64 |  |  |
| *Diabetes variables* | (0.49) | (0.47) | (0.50) | | (0.48) |  |  |
|  |  |  |  |  |  |  |
| Self-reported diabetes | 0.05 | 0.06 | 0.09 | | 0.12 |  |  |
| Diabetes duration if self- | (0.22) | (0.24) | (0.29) | | (0.32) |  |  |
|  |  |  |  |  |  |  |
| 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 |  |  |
| HbA1c ≥ 6*.*5% |  |  | (1.89) | | (2.02) |  |  |
|  |  | 0.26 | | 0.28 |  |  |
|  |  |  | (0.44) | | (0.45) |  |  |
| Undiagnosed diabetes |  |  | 0.18 | | 0.18 |  |  |
| *Education and demographic variables* |  |  | (0.39) | | (0.39) |  |  |
|  |  |  |  |  |  |  |
| 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 |  |  |
| Number of children (age < 6) | (0.50) | (0.50) | (0.49) | | (0.50) |  |  |
|  |  |  |  |  |  |  |
| 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 |  |  |

*Notes* 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.

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.

* **Estimation strategy**

Strauss and Thomas (1998) provide a useful framework to think about the relationship between health and labour market outcomes:

|  |  |
| --- | --- |
| *L* = *L*(*H, pc, w*(*H*; *S, A, B, I, α, ew*)*, S, A, B, V, ξ*) | (1) |

where *L* is labour supply or labour 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), *ew* represents the measurement error, *V* is non-labour income and *ξ* is the taste parameter.

The equation showcases the joint eﬀect of health on both wages and labour supply or labour market participation. Health aﬀects labour 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 becoming more severe 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 (Thoolen et al., 2006). We therefore expect diabetes to adversely aﬀect health and consequently labour market outcomes.

When estimating Eq. 1 empirically with observational data, unobserved heterogeneity may bias the results. As mentioned in the introduction of this chapter, 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 wages or employment status may also aﬀect the probability to develop diabetes by aﬀecting dietary and physical activity patterns. Finally, measurement error *ew* 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.

7In one of the first analyses 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.

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

1. **Panel data on self-reported diabetes**

We investigate the relationship between self-reported diabetes and three labour market outcomes: employment, wages and weekly working hours, 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 charac-teristics 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 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: |  |
| *Yit* = *β*0+ *β*1*Diabetesit* + *β*2*Xit* + *ci* + *γt* + *uit.* | (2) |

where *Yit* is a binary variable taking a value of 1 if respondent *i* reports being in employment at time *t* and 0 otherwise, *Diabetesit* is a binary variable taking a value of 1 at time *t* if the respondent reports having ever received a diagnosis of diabetes10, *Xit* is a vector of control variables, *ci* represents an individual fixed eﬀect, *γt* represents year dummies, and *uit* is the error term.

For the relationship of self-reported diabetes with wages and working hours our em-pirical models are estimated conditional on having positive wages and being employed, respectively. In these models *Yit* 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 labour market outcomes and the eﬀect of childbearing 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 in-dicators of household assets and housing conditions to create an indicator for household wealth11 (Filmer and Pritchett, 2001). Finally, a quadratic age term and calendar year

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

9See the respective table for the results of the cluster robust Hausman test

10We 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 labour market outcomes have found no asso-ciation (Minor, 2011; Minor and MacEwan, 2016). Including type 1 diabetes therefore likely attenuates any adverse relationship we may find.

11Our 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.

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 labour market outcomes. So far, the evidence of the health eﬀects of job loss does not indicate important eﬀects of job loss on the probability to develop diabetes (Bergemann et al., 2011; Schaller and Stevens, 2015), 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 (Eriksson et al., 2013; Heraclides et al., 2012). However, while stress levels may change over time, a person’s coping mechanisms to deal with stress are likely time-invariant (Schneiderman, Ironson, et al., 2005). 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 FE applied approach should then limit the bias resulting from these time-invariant confounding factors.

1. **Self-reported diabetes duration**

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

|  |  |
| --- | --- |
| *Yit* = *β*0+ *β*1*Dyearsit* + *β*2*Xit* + *ci* + *uit,* | (3) |

where *β*1*Dyearsit* is a continuous variable indicating years since first diabetes diagnosis. 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.

|  |  |
| --- | --- |
| *Yit* = *δ*0+ *g*(*Dyearsit*) + *δ*2*Xit* + *ci* + *uit.* | (4) |

with *g*(*Dyearsit*) = P*Nn*=1 *δn* ·*max*{*Dyearsit* −*ηn*−1}*Iin* and *Iin* = 1[*ηn*−1 ≤ *Dyearsit* *< ηn*], with *ηn* being the place of the *n*-th node for *n* = 1*,* 2*, . . . , N*. We choose three nodes that—

based on visual inspection (see Figures 1,  [2](#page21) and  [3](#page22) on pages , and , respectively)—best captured any possible non-linearity in the relationship between diabetes duration and labour market 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 labour market outcomes. The coeﬃcient *δn* captures the eﬀect of diabetes for the *n*-th interval. The eﬀects are linear if *δ*1 = *δ*2 =*, . . . ,* = *δn*.

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 (Wooldridge, 2012). Because this is also the case for diabetes duration, in Eq.  [(3)](#page10) and Eq.  [(4),](#page10) 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

1. **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 a 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 hypochon-driac.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 an overestimation of the impact if some of those misreports reflect other factors that negatively aﬀect labour market outcomes (e.g. other illnesses or general ill health), or if they are used to justify other adverse events that may negatively aﬀect labour market outcomes. Similarly, underreporting may lead to

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

13Consequently, 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.

14Models also excluding the calendar year dummies provide similar results.

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

an overestimation if those with undiagnosed diabetes are generally healthier, hence more likely to have positive labour 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 behaviour. Two studies found a diabetes diagnosis and subsequent treatment to increase the odds of psychological problems, including depression and anxiety (Paddison et al., 2011; Thoolen et al., 2006), while similar results have not been found for people with undiagnosed diabetes (Nouwen et al., 2011). Looking at behavioural change, health infor-mation has been shown to aﬀect behaviour after the diagnosis of not only diabetes (Slade, 2012) but also of other chronic diseases (see Baird et al. (2014), Gong (2015), Thornton (2008), and Zhao et al. (2013)). However, little is known about the eﬀects of health in-formation on labour market outcomes. For diabetes, only Liu and Zhu (2014) investigate the eﬀect of receiving a diabetes diagnosis on labour income in Chinese employees. This study finds a reduction in labour 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 labour market outcomes which can then be compared to the estimated eﬀect of self-reported diabetes. The biomarker data also enable us to look at diabetes severity, as measured by HbA1c values. Since these data are 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, the data allow for a first exploration of the relationships of measured diabetes and disease severity with labour market outcomes.

Our analysis of the biomarker sample consists of three steps. We first estimate Eq. 5 to assess the association of self-reported diabetes with labour market outcomes, as before, but this time for the biomarker sample only, using the following specification:

|  |  |
| --- | --- |
| *Yi* = *β*0+ *β*1*Dsri* + *β*2*Xi* + *ci* + *ui* | (5) |

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

|  |  |
| --- | --- |
| *Yi* = *β*0+ *β*1*Dbioi* + *β*2*Xi* + *ci* + *ui* | (6) |

Here *Dbioi* is equal to 1 if HbA1c ≥ 6*.*5%.

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

|  |  |
| --- | --- |
| and estimate: |  |
| *Yi* = *β*0+ *β*1*Dsri* + *β*2*Dbioi* + *β*3*Xi* + *vi* + *ui.* | (7) |

For the biomarker analysis we rely on within-household variation *vi* for identification to account for unobserved community characteristics, such as the access to healthcare

16In a very diﬀerent context Dillon et al. (2014), using a randomized intervention, find that the news stemming from a diagnosis of malaria aﬀect productivity and income, but not labour supply among sugar cane cutters in Nigeria.

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 labour market outcomes.17

* **Results**

1. **Incidence of self-reported diabetes**

Table 2 presents the estimation results of the FE model using Eq. 2. They indicate signifi-cant and substantial reductions in the probability of employment for men and women with self-reported diabetes. The coeﬃcients are similar for both sexes, showing a reduction in employment probabilities of over 5 percentage points. In relative terms—taking into ac-count the lower employment rates for women compared to men—these absolute reductions translate into a relative reductions in employment probabilities of 14% for women and of 6% for men, suggesting a stronger impact of diabetes on women than men.

The results in Columns 3–6 show no significant relationship between self-reported dia-betes 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.

The results in Table 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 labour market), without going through a notable phase of reduced productivity and labour supply.

To explore whether diabetes aﬀects the selection into certain types of work we estimate

17We 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 identifica-tion.

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 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. [181](#page14)9

18We also estimated a pooled multinomial logit model augmented with the within-between approach (Bell and Jones, 2015), based on the work of Mundlak (1978), which allows interpreting the coeﬃcients of all time-varying variables as within-eﬀects by including individual means of all time-varying covariates. Several other studies in economics have used this approach recently, e.g., Boll et al. (2016), Geishecker and Siedler (2011), and Wunder and Riphahn (2014). The results indicate a very similar pattern both in size and significance.

19Using 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.

Table 2: Self-reported diabetes and labour market outcomes.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Employment | |  | Log hourly wages | |  | Weekly working hours | |  |
|  |  |  |  |  |  |  |  |  |  |
|  | (1) | (2) | (3) | | (4) | (5) | | (6) |  |
|  | Males | Females |  | Males | Females |  | Males | Females |  |
|  |  |  |  | |  |  |  |  |  |
| Self-reported diabetes | −.054∗∗ | −.059∗∗ | 0.054 | | 0.081 |  | −.524 | −1.955 |  |
|  | (.025) | (.024) | (.067) | | (.158) | (1.499) | | (2.517) |  |
|  |  |  |  | |  |  | |  |  |
| Hausman test | 255.260 | 388.822 | 1084.317 | | 91.096 | 967.007 | | 106.455 |  |
| p-value | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 |  |
| N | 21388 | 27341 | 13828 | | 7068 | 17616 | | 9112 |  |

*Notes* Individual level fixed eﬀects. 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.

Table 3: Eﬀect of self-reported diabetes on wages and working hours, by type of work.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Log hourly wage | |  | Weekly working hours | |  |  |
|  |  |  |  |  |  |  |  |
|  | (1) | (2) | (3) | | (4) |  |  |
|  | Males | Females |  | Males | 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 |  |  |
| Self-reported diabetes x | (.076) | (.169) | (1.606) | | (2.252) |  |  |
| −.242 | −.409 |  | −5.495∗ | −3.535 |  |  |
| agricultural worker |  |  |  |
| Self-reported diabetes x | (.188) | (.373) | (2.833) | | (22.300) |  |  |
| −.105 |  |  |  | −4.149 |  |  |
| self-employed | 0.125 | 0.306 | |  |  |
|  | (.192) | (.326) | (2.503) | | (4.739) |  |  |
|  |  |  |  | |  |  |  |
| Hausman test | 280.491 | 912.537 | 4086.461 | | 995.171 |  |  |
| p-value | 0.000 | 0.000 | 0.000 | | 0.000 |  |  |
| N | 13828 | 7068 | 17616 | | 9112 |  |  |

*Notes* Individual level fixed eﬀects. Robust standard errors in parentheses. Reference category:non-agricultural worker or employee. Other control variables: state dummies, urbanization dum-

mies, 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.

Table 4: Relationship between self-reported diabetes and selection into types of work.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Males |  |  |  | Females |  |  |
|  |  |  |  |  |  |  |  |  |
|  | (1) | (2) | (3) | (4) | | (5) | (6) |  |
|  | Non-agric. | Agric. | Self-employed |  | Non-agric. | Agric. | Self-employed |  |
|  |  |  |  |  |  |  |  |  |
| Self-reported diabetes | −.006 | −.008 | −.043 |  | −.001 | −.022∗∗ | −.029 |  |
|  | (.029) | (.022) | (.026) | (.018) | | (.009) | (.018) |  |
|  |  |  |  |  | |  |  |  |
| Hausman test | 2196.390 | 2005.383 | 1249.080 | 1126.933 | |  | 86.400 |  |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | |  | 0.000 |  |
| N | 20719 | 20719 | 20719 | 26577 | | 26577 | 26577 |  |

*Notes* 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.

1. **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 labour 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 labour 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 labour 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 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 Figure 2). Similar trends are observed for working hours (see Figure 3).

Tables  [5](#page24) and  [6](#page25) 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)](#page10) and Eq.  [(4](#page10)).

For male employment probabilities (Table 5) the results indicate a yearly reduction throughout all models, with the biggest eﬀects being suggested by the FE model. For women, the coeﬃcient shows a reduction of up to almost 1 percentage points per year in the FE model, though though statistical significance is lower than in the ordinary least squares (OLS) models. Focusing on the FE results, 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 (Table 6), 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 for both men and women. We also find associations for women with more than 20 years of diabetes, but these estimates may be spurious due to the con-siderably reduced number of observations in this group.21 Interestingly, the reductions in wages found in the non-linear specification appear exactly at the time where employment probabilities are less aﬀected. This could suggest that at this point reductions in produc-

20Since 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.

21There are only 9 and 3 observations for male and female wages with more than 20 years since diagnosis in wave 3, respectively, and 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.

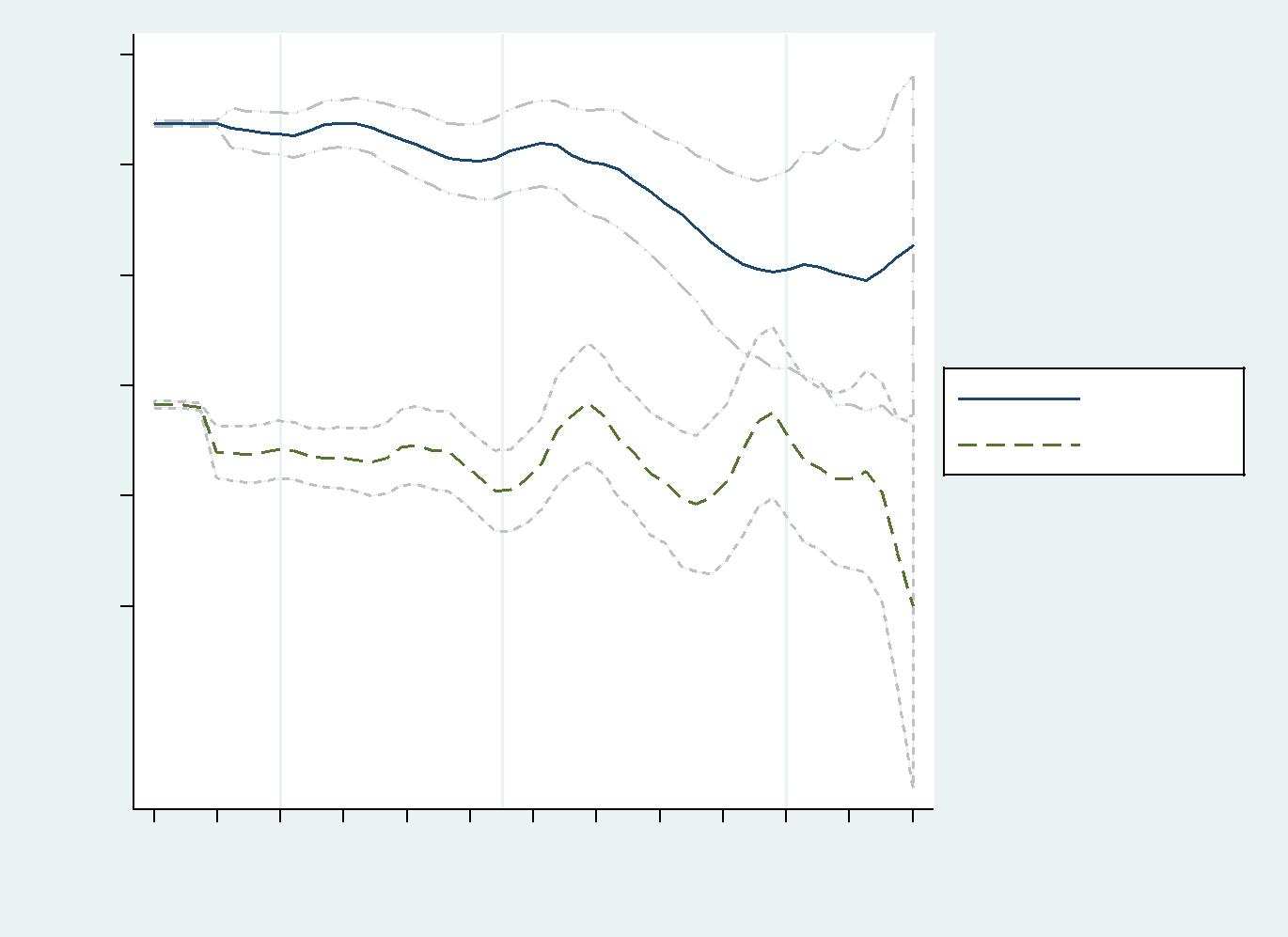
tivity aﬀect wages but are not so severe that they would cause job loss. There appears to be no consistent relationship between working hours and time since being diagnosed with diabetes.

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 percentage points for females after 11 to 15 years and a reduction of 60 percentage points 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

22We estimated a comparable model to that of Minor (2013) using dummy variables and find a significant reduction in employment probabilities 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 percentage points, depending on the specification used, 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.

Figure 1: Kernel-weighted local polynomial regression of employment status on diabetes

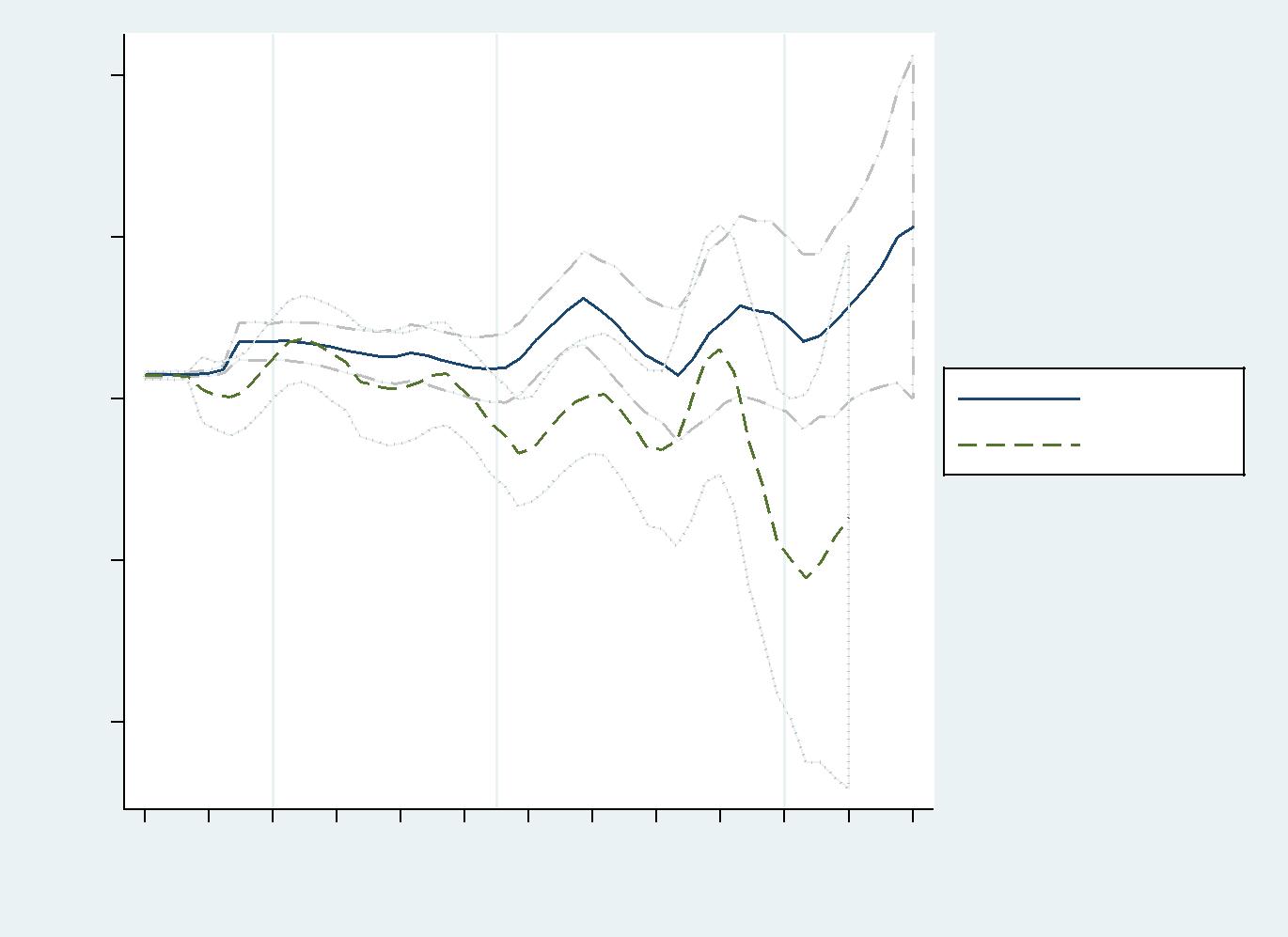
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| duration. | |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 1 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | .8 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | .6 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Employment | .4 |  |  |  |  |  |  |  |  |  |  |  | Males |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  | Females |  |
| .2 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 0 | 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 20 | 22 | 24 |  |
|  |  |  |  |  | Years since diagnosis | | | | |  |  |  |  |  |



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

Figure 2: Kernel-weighted local polynomial regression of log hourly wages on diabetes

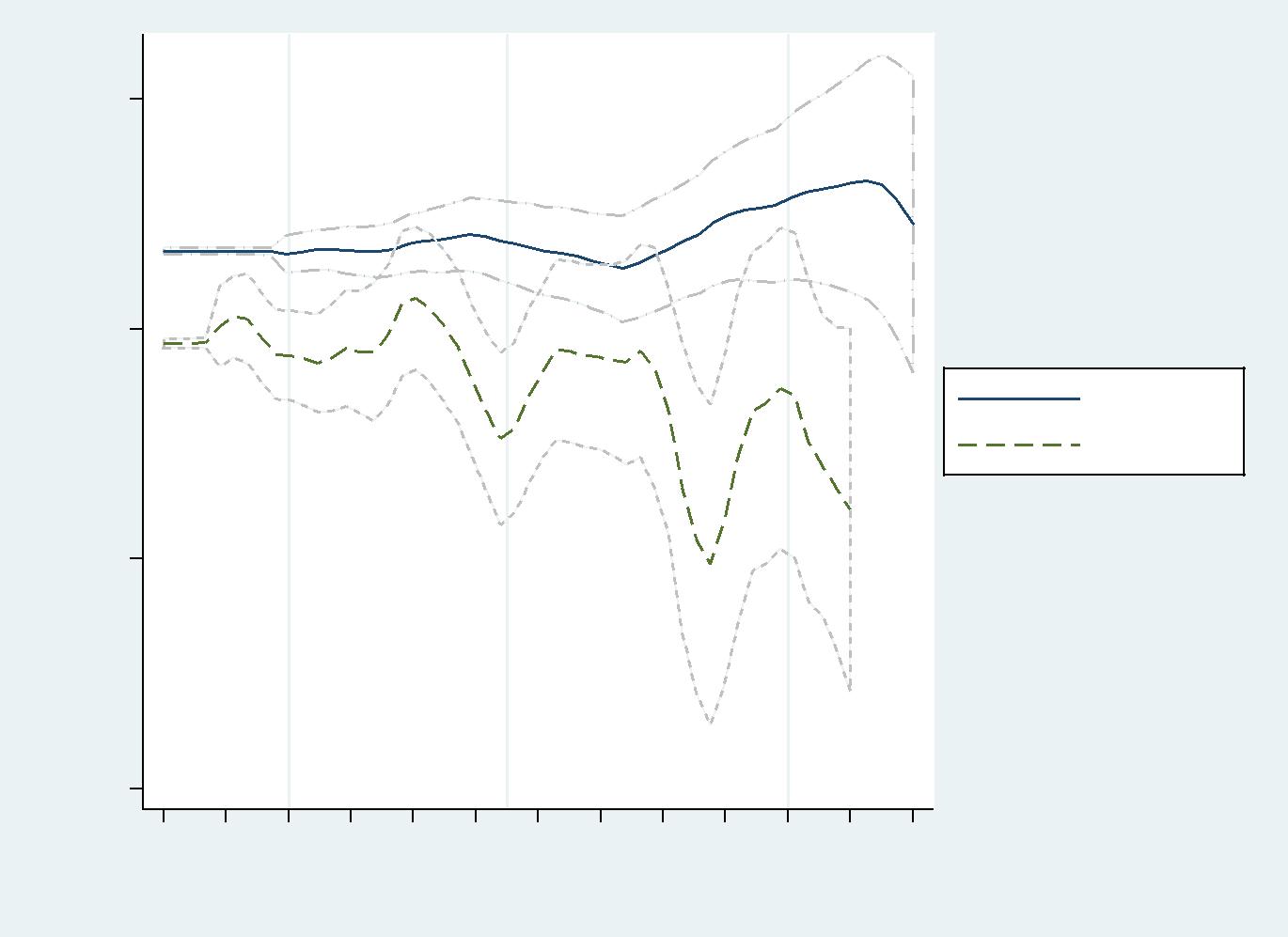
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| duration. | |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 5 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 4 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| wage |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Log hourly | 3 |  |  |  |  |  |  |  |  |  |  |  | Males |  |
|  |  |  |  |  |  |  |  |  |  |  |  | Females |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 2 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 1 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 0 | 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 20 | 22 | 24 |  |
|  |  |  |  |  | Years since diagnosis | | | | |  |  |  |  |  |



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

Figure 3: Kernel-weighted local polynomial regression of working hours on diabetes dura-

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| tion. |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 60 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| hours | 40 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| working |  |  |  |  |  |  |  |  |  |  |  |  | Males |  |
|  |  |  |  |  |  |  |  |  |  |  |  | Females |  |
| Weekly | 20 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 0 | 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 20 | 22 | 24 |  |
|  |  |  |  |  | Years since diagnosis | | | | |  |  |  |  |  |



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

1. **Cross-sectional biomarker analysis**

In this section we gain additional insights from using the biomarker data collected in the third wave of the MxFLS. 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 7). The table shows 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 the biomarker analysis, 32% self-report a diagnosis, while 68% do not.

To further investigate the relationship of self-reported and biomarker tested diabetes, we estimate the models presented in equations 5, 6 and 7. The results in columns 1 and 2 of Table 8 show that the earlier longitudinal results using self-reported diabetes 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. 7, the coeﬃcient for the biomarker diabetes population *Dbioi* 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 labour market outcomes.

23We also created a dummy variable that additionally to measured diabetes accounted for those with a self-reported diabetes diagnosis but biomarker 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 8, which is why we do not present them here.

Table 5: Relationship between self-reported years since diagnosis and employment proba-bilities using continuous duration and duration splines.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Males |  |  |  | Females |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  | (1) | (2) | (3) | (4) | | (5) | (6) |  |  |
|  | OLS | OLS | FE |  | OLS | OLS | FE |  |  |
|  | (Wave 3) | (Pooled) |  |  | (Wave 3) | (Pooled) |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Panel A: linear | −.008∗∗∗ | −.007∗∗∗ | −.017∗∗∗ |  | −.005∗∗∗ | −.004∗∗∗ | −.009∗ |  |  |
| Diabetes duration |  |  |  |
|  | (.002) | (.002) | (.006) | (.002) | | (.001) | (.005) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Hausman test |  |  | 153.024 |  |  |  | 200.073 |  |  |
| p-value |  |  | 0.000 |  |  |  | 0.000 |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Panel B: splines |  |  |  |  |  |  |  |  |  |
| Diabetes duration | −.007 | −.007 | −.026∗ |  | −.010 | −.015∗∗ | −.017 |  |  |
| 0–4 |  |  |  |
|  | (.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) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Hausman test |  |  | 161.953 |  |  |  | 198.692 |  |  |
| p-value |  |  | 0.000 |  |  |  | 0.000 |  |  |
| N | 8217 | 16292 | 16292 | 10467 | | 22407 | 22407 |  |  |

*Notes* The table presents the results of three estimation methods. Panel A presents the results of the linear specifications. PanelB 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 OLS and pooled OLS models additionally control for age. ∗ *p <* 0*.*10, ∗∗ *p <* 0*.*05, ∗∗∗ *p <* 0*.*01.

Table 6: Relationship between self-reported years since diagnosis and log hourly wage / weekly working hours using continuous duration and duration splines.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Males |  |  |  | Females |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  | (1) | (2) | (3) | (4) | | (5) | (6) |  |  |
|  | OLS | OLS | FE |  | OLS | OLS | FE |  |  |
|  | (wave 3) | (pooled) |  |  | (wave 3) | (pooled) |  |  |  |
|  |  |  |  | | |  |  |  |  |
|  |  |  | **Log hourly wages** | | |  |  |  |  |
| Panel A: linear |  |  | −.019 |  | −.014∗ | −.009 | −.073∗∗ |  |  |
| Diabetes duration | 0.001 | 0.010∗∗ |  |  |  |
|  | (.006) | (.005) | (.018) | (.008) | | (.008) | (.029) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Hausman test |  |  | 838.213 |  |  |  | 93.232 |  |  |
| p-value |  |  | 0.000 |  |  |  | 0.000 |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Panel B: splines |  |  |  |  |  |  |  |  |  |
| Diabetes duration |  |  |  |  |  |  |  |  |  |
| 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) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Hausman test |  |  | 1037.290 |  |  |  | 96.266 |  |  |
| p-value |  |  | 0.000 |  |  |  | 0.000 |  |  |
| N | 5509 | 10767 | 10767 | 2874 | | 5741 | 5741 |  |  |
|  |  |  |  | | |  |  |  |  |
|  |  |  | **Weekly working hours** | | |  |  |  |  |
| Panel A: linear |  |  |  |  | −.020 | −.124 |  |  |  |
| Diabetes duration | 0.069 | 0.048 | 0.181 |  | 0.208 |  |  |
|  | (.124) | (.102) | (.330) | (.187) | | (.127) | (.652) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Hausman test |  |  | 704.904 |  |  |  | 107.709 |  |  |
| p-value |  |  | 0.000 |  |  |  | 0.000 |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Panel B: splines |  |  |  |  |  |  |  |  |  |
| Diabetes duration | −.033 | −.233 |  |  |  |  |  |  |  |
| 0–4 | 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) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Hausman test |  |  | 724.225 |  |  |  | 112.627 |  |  |
| p-value |  |  | 0.000 |  |  |  | 0.000 |  |  |
| N | 6807 | 13581 | 13581 | 3591 | | 7383 | 7383 |  |  |

*Notes* The table presents the results of three estimation methods for the two dependent variables: log hourly wagesand 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, calendar year dummies, type of

work (agricultural and self employed with dependent non-agricultural wage employment as the base) and health insurance status. The OLS and pooled OLS models additionally control for age. ∗ *p <* 0*.*10, ∗∗ *p <* 0*.*05, ∗∗∗ *p <* 0*.*01.

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, with higher HbA1c levels or a longer disease duration are more likely to go to the doctor and 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 estimate models accounting for measured HbA1c levels, to investigate in how far current diabetes severity aﬀects our labour market outcomes. If current severity would be related to labour market outcomes and explain the diﬀerence between self-reported and the undiagnosed diabetes population, one would expect an adverse association with increasing HbA1c levels, for both self-reporting and undiagnosed. To investigate this, we construct three dummy variables using HbA1c groups above the diabetes threshold (i.e. 6.5–7.9, 8–11.9 and 12– 14), each for those with self-reported diabetes and for those unaware of their diabetes (Table 9, Panel B).

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 9, Panel A). Especially for women, the point estimates for self-reported diabetes and undiagnosed diabetes are now virtually the same size, suggesting that diﬀerences could be due to the diﬀerences in self-reported health. For men, factors not captured by self-reported health may still play a role. 24

Turning to Panel B, we do not find a consistent relationship of increasing HbA1c levels with employment chances, especially for those self-reporting, suggesting that current disease severity may not explain the diﬀerent employment eﬀects of diabetes for the aware and unaware.

To the best of our knowledge only one study has previously used biomarkers to analyse the relationship with labour 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 labour 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 labour 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.

(Minor and MacEwan, 2016) finds for a general USA population, similar to us, that people with undiagnosed diabetes likely, if at all, experience smaller employment penalties than people self-reporting the disease. He finds, however, much bigger eﬀects then we do when estimating the impact of biometrically measured diabetes instead of distinguishing between the self-reporting and those unaware. This may be explained by the fact that in that study the undiagnosed population made up a much smaller share of the overall diabetes population compared to our study, so that self-reported diabetes was still the

24Additionally accounting for measures of overweight and obesity, self-reported hypertension, heart disease and depression does not further aﬀect the interpretation of the diabetes coeﬃcient.

Table 7: Number of observations with diabetes (HbA1c ≥ 6*.*5%) and self-reported diabetes.

|  |  |  |  |
| --- | --- | --- | --- |
|  | *HbA*1*c <* 6*.*5% | HbA1c ≥ 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% |

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

Table 8: Biomarker results

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Self-reported diabetes | |  | HbA1c ≥ 6.5 | |  | HbA1c ≥ 6.5 and self-reported d. | |  |  |
|  | (1) | (2) |  | (3) | (4) |  | (5) | (6) |  |  |
|  | Males | Females |  | Males | Females |  | Males | Females |  |  |
|  | | |  |  |  |  |  |  |  |  |
| **Dependent variable: Employment** | | |  |  |  |  | −.053∗∗ | −.032 |  |  |
| Self-reported diabetes | −.051∗∗ | −.044∗ |  |  |  |  |  |  |
| HbA1c ≥ 6.5 | (.026) | (.023) |  | −.012 | −.031∗ | (.026) | | (.026) |  |  |
|  |  |  | 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 |  |  |
| HbA1c ≥ 6.5 | (.065) | (.113) |  | −.007 | −.057 | (.078) | | (.119) |  |  |
|  |  |  |  | −.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 |  |  |
| HbA1c ≥ 6.5 | (1.305) | (2.178) |  | −.088 |  | (1.419) | | (2.351) |  |  |
|  |  |  | 1.153 |  | −.012 | 1.525 |  |  |
|  |  |  | (.844) | | (1.462) | (.925) | | (1.565) |  |  |

*Notes* Community level fixed eﬀects. Robust standard errors in parentheses. Other control variables: age, age squared, statedummies, 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.

Table 9: Self-reported diabetes, biomarkers, diabetes severity and self-reported health and their association with labour market outcomes

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Employment | |  | Log hourly wages | |  | Weekly working hours | |  |  |
|  |  |  |  |  |  |  |  |  |  |  |
|  | (1) | (2) | (3) | | (4) | (5) | | (6) |  |  |
|  | Males | Females |  | Males | Females |  | Males | Females |  |  |
|  | | |  |  |  |  |  |  |  |  |
| **Panel A (self-reported health)** | | |  |  |  |  |  | −2.191 |  |  |
| Self-reported diabetes | −.036 | −.023 | 0.002 | | 0.060 | 0.123 | |  |  |
| Hba1c ≥ 6*.*5% | (.026) | (.027) | (.079) | | (.121) | (1.433) | | (2.386) |  |  |
| 0.003 | −.023 |  | −.004 | −.051 |  | −.066 | 1.829 |  |  |
|  | (.017) | (.019) | (.049) | | (.075) | (.926) | | (1.569) |  |  |
| Self-reported health status | |  |  |  | −.115 |  | −1.131 |  |  |  |
| good | 0.023 | 0.057∗ | 0.061 | |  | 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 | −.126∗∗ | −.040 |  | −.228∗ |  |  |  | −9.170∗ |  |  |
| 6*.*5 − 7*.*9 |  | 0.041 | 1.218 | |  |  |
| 8 − 11*.*9 | (.059) | (.051) | (.127) | | (.269) | (2.921) | | (4.864) |  |  |
| −.052 | −.051 | 0.026 | | 0.225 |  | −1.332 | −1.086 |  |  |
|  | (.051) | (.042) | (.107) | | (.206) | (2.298) | | (4.395) |  |  |
| 12+ | 0.011 | 0.021 |  | −.106 | −.427 | 1.979 | | −2.518 |  |  |
| Undiagnosed diabetes | (.062) | (.069) | (.156) | | (.279) | (3.692) | | (5.335) |  |  |
|  | −.002 |  |  | −.040 |  |  |  |  |  |
| 6*.*5 − 7*.*9 | 0.005 | 0.015 | | 1.003 | | 3.616 |  |  |
| 8 − 11*.*9 | (.022) | (.025) | (.058) | | (.099) | (1.178) | | (2.323) |  |  |
| 0.006 | −.027 | 0.014 | | −.204 |  | −1.004 | −.077 |  |  |
|  | (.035) | (.031) | (.078) | | (.129) | (1.485) | | (2.614) |  |  |
| 12+ | 0.015 | −.055 |  | −.019 | 0.169 |  | −1.581 | 1.753 |  |  |
|  | (.040) | (.046) | (.087) | | (.181) | (2.099) | | (3.978) |  |  |
|  |  |  |  | |  |  | |  |  |  |
| N | 2785 | 3623 | 1803 | | 884 | 2302 | | 1144 |  |  |

*Notes* 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.

predominant factor driving the result.

* **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 longi-tudinal 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 labour 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 cancelling out the potential role of unobserved individual traits that may aﬀect both labour 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 labour 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 labour 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 (Adler et al., 2003). Looking at wages as our labour market outcome, we uncover some adverse eﬀects for females, indicating a sizeable 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 (Hu, 2011; 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 labour 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 labour 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 either, 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.

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 for those with self-reported diabetes 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 labour 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 (Bratti and Mendola, 2014). 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 (Colchero et al., 2016), though the long-term eﬀects in terms of diabetes prevention remain to be demonstrated.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.

**Appendix**

* **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 mis-reporting 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) (Yuan et al., 2015). 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 ≥ 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 10

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-

Table 10: 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 |

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≥ 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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