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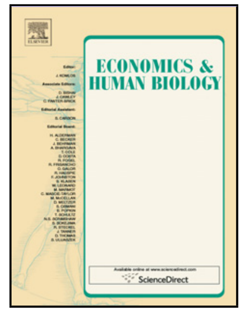

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<AT>Performance of people with diabetes in the labor market: An empirical approach controlling for complications

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<ABS-HEAD>HIGHLIGHTS► We improve the existing literature by controlling for diabetes-related complications. ► Diabetics have poorer outcomes in terms of unemployment status and income. ► There are mixed outcomes, depending on age and gender. ► The burden of diabetes is mediated by clinical and functional complications. ► Our findings have important implications for research and policy to reduce health inequalities.

<ABS-HEAD>Abstract

<ABS-P>This paper introduces a framework for modelling the impact that diabetes has on employment status and wages, improving the existing literature by controlling for diabetes-related complications. Using the last wave of the Spanish National Health Survey, we find that 1,710 adults out of the original sample of 36,087 have diabetes, reporting higher rates of unemployment. Our empirical results suggest that persons with diabetes, compared with non-diabetic persons, have poorer labor outcomes in terms of length of unemployment and lower income. However, diabetes is not significantly associated with unemployment probabilities, suggesting that the burden of diabetes on employment is mediated by lifestyle factors and clinical and functional complications. In addition, there are mixed outcomes to this econometric approach, depending on age and gender, among other factors. This interesting finding has several implications for research and policy on strategies to get lower health inequalities.

<ABS-P>**JEL Codes:** I00; I10; I14; J01

<KWD>Keywords: Health; Chronic disease; Diabetes; Earnings; Employment

<H1>1. Introduction

Burden of Diabetes has been ranked as the seventh and eighth cause of years of life lost and Disability-Adjusted Life Years (DALYs), respectively, in Western Societies (Murray and López, 2013) and the 14th cause all over the world in the ranking of causes of DALYs (Murray *et al.*, 2012), accounting for 1.9% of total DALYs and with an increase of more than 60% in 2010 as compared with the data obtained in 1990. Moreover, the number of patients with diabetes has rapidly increased globally, being projected to reach 4.8% of the whole population in the year 2030 compared to the 2.8% estimated in 2000. A huge proportion of its significant increase is due to the rise of the prevalence of type 2 diabetes mellitus (T2DM), being estimated to concern around 380 million people by 2025 all over the world (O'Shea *et al.*, 2013). This increase will be led by the older adults (Sloan *et al.*, 2008), who represent around 50% of the people with diabetes and whose prevalence of this disease is near 25% (Soriguer *et al.*, 2012). In fact, population ageing, together with greater levels of obesity, will make T2DM approach epidemic proportions globally.

Taking into account that the population ageing is one of the two more relevant factors (jointly to the population growth) in generating the increase in DALYs due to Non Chronic Diseases (NCDs), and that there is a shift to burden older ages and a tendency to a greater weight of years lived with disability in determining DALYs, it is forecasted an increasingly role for chronic diseases that generates disabling conditions (like diabetes) on the burden of disease (Sloan et al., 2008).

Such disabling condition derived from diabetes could have implications not only on the quality of life of its patients, but also on their employment status, working hours or wages (Chu *et al.*, 2001; Vijan *et al.*, 2004; Bolin *et al.*, 2009). However, assessing the impact of diabetes on productivity is not so straightforward, since its effect on individual's health is usually mediated by the complications that people with diabetes develop, both clinical and functional.

Actually, diabetes can impact employment in several ways. Diabetes complications might weaken the ability to work, forcing early retirement (Norlund *et al.*, 2001; Herquelot *et al.*, 2011; Rumball-Smith *et al.*, 2014), increase absenteeism (the number of work days lost due to health concerns) as Tunceli *et al.* (2005) or Hex *et al.* (2012) show, or decrease productivity at work (Hex *et al.*, 2012; American Diabetes Association, 2013).

Moreover, employers could hinder diabetic people work performance limiting the type of work they can do due to their concerns about their lower productivity (Songer *et al.*, 1989). A useful framework for understanding this effect is the US evidence that provides different results. Mayfield *et al.* (1999) showed that the 1,502 individuals with diabetes included in their analysis had more work-loss days than the non-diabetic sample, composed by 20,405 people, leading to significantly lower earnings for the former group, $4.7 million loss in 1987. Valdmanis *et al.* (2001) concluded that persons with diabetes had, on average, 5.2 days of work-loss days compared with 1.3 days for the non-diabetic group.

Furthermore, the unemployment rate within the subsample with diabetes was 16% against the 3% in the comparison group, as well as a reduction in their annual income. When differentiating by gender, Yassin *et al.* (2002) showed that both men and women with diabetes had more mean disability days than their counterparts, being this difference of 3.1 more lost work days per year, on average, in case of men and of 0.6 for women (American Diabetes Association, 2003).

Duration of diabetes also has a negative effect on productivity at work, increasing as the number of years since diagnosis also increases (Lavigne *et al.*, 2003). Such association between time since diabetes diagnosis and productivity has been analyzed elsewhere, concluding that the likelihood of being employed decreased shortly after diagnosis and after around 10 years for females (Minor, 2013). Another study using data from a longitudinal sample of 7,055 employees aged 51-61 years old from years 1992 to 1994 concluded that among individuals with diabetes, the absolute probability of working was 4.4 percentage points less for women and 7.1 less for men relative to that of their counterparts without diabetes (Tunceli *et al.*, 2005). Furthermore, the American Diabetes Association (2012) has calculated the total value of lost productivity due to diabetes, which reached $68.6 billion, accounting for around one third of these costs to permanent disability by diabetes. The study also shows that diabetes increased early-retirement probability by 2.4 percentage point due to disability, although this figure is reduced by a later study to 1.40 (Rumball-Smith *et al.*, 2014).

Estimates from Australian subsamples have reported as well a negative association between diabetes and labor market outcomes. Schofield *et al.* (2014) reported that those who were early retired as a result of diabetes had a median annual income of $11,784, which was half of the median annual income of part-time employees with no chronic condition and about one fifth of the annual income of those workers full time with no chronic condition, leading to $383.9 million in lost income earnings by those with diabetes. In a later study, Schofield *et al.* (2015) confirmed that there were significant differences in income between the people who retired due to their diabetes and the healthy population, having 95.5% less total savings and 95.5% less total income at age 65.

Some results can also be found with regards to European countries. Within a subsample of 1,677 Swedish patients with diabetes mellitus, the average number of work-loss days was 21.4 days per year per individual (Norlund *et al.*, 2001). Using a smaller sample of Bulgarians, 38 people with diabetes and 100 individuals without the disease, Plaveev *et al.* (2006) showed that the diabetics were more likely to be absent from work than the control group. Another study from Sweden estimated the economic impact of diabetes and concluded that the reduction in earnings due to premature mortality increased from €62 in 1987 to €157 in 2005 and from €123 in 1987 to €426 in 2005 as a result of illness-dependent early retirement (Bolin *et al.*, 2009). Similarly, Persson *et al.* (2016) examined the effect of the onset of diabetes before 15 years of age on labor market outcomes and contributed to the literature on effects of childhood health on adult socioeconomic status using national Swedish socioeconomic register data. They found that diabetes in childhood had a negative effect on labor market outcomes later in life. Part of the diabetes effect was channeled through occupational field. These findings suggest that causality in the correlation between health and socioeconomic status, at least partly, was explained by an effect from health to earnings, which had implications for both the individual and society.

In another study, with a French cohort of 506 employees with diabetes and 2,530 without the disease, the probability of being employed was lower in the diabetic group (51.9 and 10.1% at 55 and 60 years, respectively) compared with their counterparts (66.5 and 13.4%, respectively). The risk of becoming disabled, early-retirement and premature death was higher in the individuals with diabetes (Herquelot *et al.*, 2011).

More specifically, in a pooled analysis of 15 European countries, Rumball-Smith *et al.* (2014) showed that having diabetes increased the risk of early labor-force exit, reporting consistent results across countries, although the greatest probabilities of early-retirement were observed in Spain (HR: 1.52) and Ireland (HR: 1.54). Actually, in Spain, the total cost of productivity loss due to diabetes was projected to be €2.8 billion in 2009 (López-Bastida *et al.*, 2013). When estimating the number of work lost due to diabetes, these reached 154,214 days due to temporary disability generated by diabetes and its complications (Vicente-Herrero *et al.*, 2013). So, as far as we're concerned, the literature focusing on the labor market impact of diabetes is not large in Spain.

Although it is well-known that diabetes impact is mediated by its complications, these have not traditionally been included when assessing the effect of diabetes on productivity. Only a few studies have controlled for the number of diabetes complications (Lavigne *et al.*, 2003; Tunceli *et al.*, 2005) or each diabetes-related comorbidity (Bolin *et al.*, 2009). This strand of literature has been shown in Chu et al. (2001) that used data from the National Health Interview Survey (year 1989) and authors reported that self-reported diabetes had no significant effect on work-loss days, but did the diabetes-related complications, which were also the drivers for a decrease of more than $5,000 in income within the diabetic population. Actually, some authors have suggested that the estimated cost of diabetes is 2.5 times higher if comorbidity is considered (Norlund *et al.*, 2001).

The aim of this study is to assess the impact that diabetes has on employment status and wages in the Spanish population, improving the existing and recent literature by controlling for diabetes-related complications (Persson *et al.*, 2016). We use the last wave of the Spanish National Health Survey, which includes data on 21,508 households. It is a cross-sectional survey that provides information on sociodemographic characteristics, physical and mental health, variables related to lifestyle, chronic diseases and health care utilization.

We attempt to contribute to the literature in several dimensions: Firstly, we improve the existing evidence on the association between diabetes and labor outcomes by using data with more informative health information which allows controlling for health conditions, both non-related and related to diabetes, and functional status in a more detailed way. Secondly, the more detailed diabetes information allows to some extent to measure the net impact of diabetes, together with the assessment of the mediation effect that clinical and functional complications might have on employment status and wages, i.e. to investigate how the effects depend not only on diabetes, but also on its comorbidities and related functional limitations.

The structure of the paper is as follows. In Section 2 we describe the data and construction of the key attributes of labor outcomes. Then, in Section 3, the econometric model is set within the context of our data. Empirical results are presented in Section 4, including discussion of the main findings, and Section 5 concludes. Finally, there are several appendices that include background information.

<H1>2. Data description

<H2>2.1 The Spanish National Health Survey

The empirical analysis relies on the Spanish National Health Survey (SNHS) that is a widely used research operation carried out by the Spanish National Institute of Statistics in partnership with the Ministry of Public Health, Social Services and Equality. Comparable to other European health surveys, it focuses on households. At this regard, we use the 2011-2012 survey because it is the available one for last period and focused on period of the Great Recession<xps:span class="xps_endnote">1</xps:span>.

Sample selection is divided into three different stages. The unit of the first stage is the census section, which refers to January 2011. In the second phase, households are taken into account. Within each household, an adult aged 15 years old or above is selected to fill in the questionnaire and, in case of being minors (0 – 14 years old), one of them is chosen to fill in the questionnaire of minors. A third stage includes those who can be eligible for the survey within the households at the moment of the interview.

Thus, 21,508 households are part of the survey, from which interviews were made from July 2011 to June 2012. The SNHS is a cross-sectional survey that includes household and individual information on sociodemographic characteristics (age, gender, region, educational level, employment status and household income), healthy lifestyles (tobacco and alcohol consumption, weight and height), as well as chronic diseases and use of healthcare resources.

Two main variables are object of study in the present analysis: being unemployed and household income. Regarding the former outcome, respondents are asked about their employment status, having to choose between employed, unemployed, retired, studying, permanently disabled to work and being a homemaker. From these options, we use being unemployed as our first main variable. Unemployed would be defined as those individuals aged 18 to 65 years old who are in labor force, but do not have a job and are looking for work. Moreover, we also have information on the unemployment duration, which is divided into four categories, as Table 1 shows. On the other hand, household income refers to the net income that the household receives per month. It is measured in intervals: i) less than 550€; ii) 551 – 800€; iii) 801 – 1050€; iv) 1051 – 1300€; v) 1301 – 1550€; vi) 1551 – 1850€; vii) 1851 – 2250€; viii) 2251 – 2700€; ix) 2701 – 3450€.

As the main independent variable of interest, we focus on having diabetes, which is defined as answering affirmatively to the following questions: ``Have you ever suffered from diabetes?'' and ``Have you ever consumed diabetes drugs in the last two weeks?'' We also include a list of chronic diseases; some of them are diabetes-related complications: hypertension, heart attack, arthritis, back pain, asthma, chronic lung disease, gastric ulcer, cholesterol, stroke and cancer. In order to control for functional limitations, we include a dichotomous variable which refers to the limitation in performing the basic activities of daily living (ADL) due to health problems. Moreover, we control for age, gender, educational level, marital status, overweight and obesity, and smoking habits.

<H2>2.2 Summary statistics

In the main analysis, we consider the population aged between 18 and 65 years old since it comprises the adult population within the legal working age in Spain. Summary statistics are reported in Table 1.

Our sample consisted of 36,087 individuals<xps:span class="xps_endnote">2</xps:span>, of whom 1,710 are identified as having diabetes, who represent 5% of the whole sample. From those, 93% have answered that they suffer from diabetes during the last twelve months.
We observe that people with diabetes report similar unemployment rates than the ones without the disease (20% vs 21%, respectively), being the period spent unemployed also similar in both groups and only significant for length of unemployment below one year. Moreover, the group of people without diabetes turns to have higher household income, but differences are only significant for income figures lower than 1,300€ per month. Differences in unemployment probabilities and household income are confirmed by looking at the Figure 1, which shows that within the sample with diabetes, a great number of them report having monthly incomes below 800€ and to have higher rates of unemployment.
Individuals with diabetes are also older (53.29 vs 41.99 years old), less likely to be women (43% vs 51%) and with lower educational level, as 66% of those with diabetes have completed compulsory secondary education as their maximum training degree. Moreover, people with diabetes are more likely to have overweight and obesity, as well as having ever smoked. However, they seem to be more likely to quit smoking, given the lower prevalence of current smokers within the group with diabetes compared to those without it (29% vs 20%). Furthermore, those without diabetes are less prone to be married.
With regards to health status, it seems to be always worse in those who report having diabetes, regardless of whether it is prevalence of chronic diseases or functional status. For example, the percentages of people with diabetes reporting to suffer from hypertension, chronic lung disease, stroke or cancer are 48%, 10%, 2% and 4%, respectively, in comparison to the group of respondents who do not have diabetes: 14%, 3%, 1% and 2%.

<H1>3. Methodology

<H2>3.1 Conceptual framework

In 1972, Michael Grossman (Grossman, 1972) constructed a model of the demand for the commodity "good health". It is not medical care as such what the consumer wants, but rather health. People want health; they demand input (i.e. medical care) to produce it. Health is consequently produced as well as consumed with inputs that include goods and time. So, health is a durable good that depreciates like any capital product, but can be increased through investment. Hence, individuals demand health for two reasons: consumption and investment. As a consumption commodity, health enters the utility function directly since the individual gains utility from being healthy. As an investment commodity, it determines the amount of time available for other activities, such as work or training improvements, to create future income and wealth.
The central proposition of our model is that health can be viewed as a durable capital stock that produces an output of healthy time. It is assumed that individuals inherit an initial stock of health that depreciates with age and it can be increased by investment.

Let the utility function of a typical consumer with a life horizon of *n* periods be:

$$U = U(\varphi_0, H_0, \ldots, \varphi_n H_n, Z_0, \ldots, Z_n) = U(h_t, Z_t) \quad (1)$$

where U represents the consumer's utility as a function of health (H) and other consumption (Z), H_t is the stock of health in period *t*, φ_t represents the number of healthy days per unit of H_t, $h_t = H_t \varphi_t$ denotes the total consumption of ``health services" (total number of healthy days), Z_t is the total consumption of another commodity in period *t*, and (H_0, Z_0) represent the initial stocks of health and consumption.
The equilibrium quantities of H_t and Z_t can be found by maximizing the utility function subject to the budget and time constraints and full wealth constraint. From the point of view of the individual, both market goods and own time is considered as scarce resources. The goods budget

constraint equates the present value of outlays on goods to the present value of earnings income over the life cycle plus initial assets (discounted property income).

$$\Sigma \frac{P_t M_t + V_t X_t}{(1+r)^t} = \Sigma \frac{W_t TW_t}{(1+r)^t} + A_0 \qquad (2)$$

where P_t and V_t are the prices of M_t, which refers to medical care, and X_t, which is the goods input in the production of the commodity Z; W_t is the wage rate, TW_t is hours of work, A_0 is discounted property income, and r is the interest rate. The time constraint requires that the total amount of time available in any time period must be exhausted by all possible uses.
In this model, it is assumed that, from 365 days available in a year, an individual can buy market goods such as medical care, M, or other goods, X. The person is assumed to invest some of the time available for work, Tw, and some of this time might be taken over by ill health, TI. Therefore, the time spent producing health is given by

Total time =T= 365 days = TH (improving health) + TB (producing home goods) + TL (lost to illness) + TW (devoted to work) (3)

By substituting TWi from equation (3) into equation (2), the single ``full wealth" constraint is obtained:

$$\Sigma \frac{P_t M_t + V_t X_t + W_t(TL_t + TH_t + T_t)}{(1+r)^t} = \Sigma \frac{W_t \Omega}{(1+r)^t} + A_0 = R \qquad (4)$$

where Ω = 365 days in a given year.

According to this equation, full wealth equals initial assets plus the present value of the earnings an individual would obtain if he spent all of his time at work. Part of this wealth is spent on market goods, part of it is spent on nonmarket production time, and part of it is lost due to illness. The equilibrium quantities of H_t and Z_t can now be found by maximizing the utility function subject to the full wealth constraint. Since the inherited stock of health and the rates of depreciation are given, the optimal quantities of gross investment determine the optimal quantities of health capital.
Therefore, an increase in ``bad health" due to a health disease as diabetes would have the following consequences: first of all, the number of days lost to illness would increase, leading to a decrease in number of days available to work. Secondly, job earnings would be diminished due to less time devoted to work and, moreover, the individual's utility would decrease because of the ``bad health" status due to diabetes. Besides, increased absenteeism and reduced work capacity due to diabetes-related complications should also be assumed.

3.2 Estimating the impact of diabetes on labor outcomes

We aim to assess the impact of diabetes and diabetes-related complications on two labor outcomes: employment status and earnings. In case of the former outcome, due to its dichotomous feature (being unemployed or not), we estimate the following probit model<xps:span class="xps_endnote">3</xps:span>:

$$\Pr[unemployed_i = 1\,|x_i] = \Phi\,(\beta_0 + \beta_1 diabetes_i + \beta_2 X_i + \varepsilon_i \quad (5)$$

where $unemployed_i$ is a binary variable that takes value 1 if the individual *i* is unemployed and 0 otherwise; Φ refers to Cumulative Distribution Function (CDF) of the standard normal distribution; $diabetes_i$ is a dichotomous variable that takes value 1 if the individual has reported to have diabetes and 0 otherwise; X_i is a vector of sociodemographic variables, such as age, gender, marital status, education and some lifestyle indicators (obesity, overweight, current smoker and have ever smoked); and ε_i represents the error term.

Regarding the association between suffering from diabetes and earnings, we will estimate the ordered probit model as follows, assuming the ordered nature of the variable household income in our dataset:

$$prob_i(income_1) = \Phi(\alpha_1 - \beta_1 diabetes_i - \beta_j X_i)$$

$$prob_i(income_j) = \Phi(\alpha_j - \beta_j diabetes_i - \beta_j X_i) - \Phi(\alpha_{j-1} - \beta_{j-1} diabetes_i - \beta_j X_i), j = 2, \dots, j-1$$

$$prob_i(income_J) = 1 - \sum_{j=1}^{J-1} prob_i(income_j) \qquad (6)$$

where $prob_i(income_J)$ is the probability that subject *i* (i = 1, …, I) belongs to category of income *j*.

Our empirical strategy sequentially adds variables to eq. (5) and (6) that refer to first of all, non-diabetes related complications and, then, diabetes-related complications, both clinical and functional, to test whether the impact of diabetes is mediated by them. In our baseline model, Model A, we only include diabetes and a set of sociodemographic characteristics, such as age, gender, education, being married and having obesity or overweight, and being current smoker or having ever smoked. In a second model, Model B, we will add non-diabetes related complications, which are arthritis, back pain, asthma, chronic lung disease and ulcer. Subsequently, Model C will additionally include as covariates those comorbidities that are related to diabetes: hypertension, heart attack, cholesterol and stroke. Finally, in Model D, being limited in the performance of ADLs due to health problems will be added.

Finally, since more disaggregation of the data allows for more accurate projections of the overall effect of diabetes, the sample will be divided into gender (males and females) and age groups, as some differences can be observed with regards to being unemployed across gender and age, as Figure 2 shows.

<H2>3.3 Diabetes and duration of unemployment

As it has been aforementioned, unemployment duration is larger in the subsample of people with diabetes than in those without the disease (Table 1). Thus, we will assess the influence of suffering from diabetes on the duration of unemployment status. Since it is a variable divided into categories (unemployed for less than 6 months, from 6 months to 1 year, between 1 and 2 years, and for more than 2 years), we will estimate the ordered probit model as follows:

$$prob_i(duration\_unemp_1) = \Phi(\alpha_1 - \beta_1 diabetes_i - \beta_j X_i)$$

$$prob_i(duration\_unemp_j) = \Phi(\alpha_j - \beta_j diabetes_i - \beta_j X_i) - \Phi(\alpha_{j-1} - \beta_{j-1} diabetes_i - \beta_j X_i), j = 2, \dots, j-1$$

$$prob_i(income_J) = 1 - \sum_{j=1}^{J-1} prob_i(income_j) \qquad (7)$$

where $prob_i(duration\_unemp_1)$ is the probability that subject *i* (*i* = 1, …, I) belongs to category of duration of unemployment *j*.

Subsequent variables will be added to equation 7 as it has been explained in the previous section.

<H1>4 Empirical results

This section presents estimates of the impact on labor market outcomes due to the Great Recession when focusing on diabetes conditions. Regarding the identification, several points need to be made.

First of all, diabetes is self-reported by respondents, possibly leading to recall bias. However, we aim to correct such bias by including also as people with diabetes those who answered affirmatively to the question about whether they take drugs for diabetes. Furthermore, it was not possible to distinguish by diabetes type I, which is diagnosed earlier in life, and type II diabetes, whose onset commonly takes place in later ages. To overcome this drawback, it would have been good to have information on age at onset, as other authors have already done (Minor, 2013), or type of drugs taken for diabetes. However, we didn't have such information either. Thus, we will split the sample into age groups, as it has already been mentioned, suggesting that those younger individuals with diabetes will be more likely to suffer from type I diabetes and increasingly report type II diabetes as respondents get older.

Moreover, some endogeneity issues should also be mentioned. As some authors have already reported (Brown *et al.*, 2005; Latif, 2009), endogeneity in diabetes prevalence should be taken into account when measuring the impact of diabetes. They used as instrumental variable the family history of diabetes, given the genetic predisposition component of diabetes, or parents educational level and labor market status, to control for socioeconomic background factors. However, we did not have such information in our dataset, which could be implemented in further research. What we could do is using other health issues which could be related to the development of diabetes. Moreover, we have also dropped non-Spanish nationalities from the sample, given their high diabetes incidence rate (American Diabetes Association, 2015), which could bias our estimations too.

In addition, all the other health conditions, both clinical and limitations in ADL, are also self-reported and self-reporting could bias the results and, hence, the results here could over or underestimate the true impact of diabetes. Nevertheless, previous authors have already stated that data from health conditions collected using self-reporting information is reliable (Dal Grande *et al.*, 2012; Goebeler *et al.*, 2007).

Finally, the data belongs to the SNHS from years 2011/12, but no data is available for periods before the crisis to estimate transitions to unemployment from before and after the Great Recession. However, we do have information about the length of unemployment in SNHS for Spain, which we will also use as an outcome variable.

<H2>4.1 Diabetes and (un)employment status

Table 2 shows the average marginal effects from the probit regression models applied to the probability of being unemployed.

Model A shows that diabetes has no significant effect on the outcome. Greater age (Average Marginal Effect (AME) -0.2 percentage points), being a woman (AME -0.8 percentage points), higher education levels and being married (AME -4 percentage points) are the set of socioeconomic factors that are significantly protective against unemployment. On the other hand, having completed only compulsory secondary education (AME Educ2 4.3 percentage points), having overweight (AME 1.6 percentage points), obesity (AME 4.6 percentage points), being a current smoker (AME 6.5 percentage points) or having ever smoked (AME 1.9 percentage points) significantly increase the risk of being unemployed. The same trend holds when non-diabetes related complications are included in the regression, Model B.

Moreover, when clinical (Model C) and functional complications (Model D) are included, suffering from gastric ulcer (AME 6.4 and 6.3, respectively) bears the highest probability within the chronic diseases increasing the risk of being unemployed. Regarding the socioeconomic variables and, as in models A and B, the same pattern holds in model C and D.

Moreover, the results obtained could be compared to the work by Rumball-Smith *et al.* (2014), who measured the effect of diabetes on early-labor force exit in 16 high-income countries, Spain between those. They found that the probability of their outcome in the Spanish population was higher in the people with diabetes than those without disease (HR: 1.52), confirming the significant role of diabetes on employment status, without considering any other health factor in their analysis. Same results were also reported by Herquelot *et al.* (2011), diabetes increasing the risk of early-retirement and disability in a French population by HR: 1.6 and HR: 1.7, respectively. The results might differ because of the different sample composition and having excluded in their study lifestyle factors and clinical and functional complications as they only controlled for age, gender and education.

Similar result to ours in terms of the non-significance of diabetes can be found somewhere else (Latif, 2009), showing that assessing the effect of diabetes solely on the probability on work could be overestimating its impact.

<H3>4.1.1 Subgroup analysis

<H4>4.1.1.1 By gender

Table S2 included in the Appendix shows the results from regression models A and D for females and males. Diabetes stands as a significant predictor of unemployment for males in Model A, when diabetes is the only health factor included. Hence, diabetes increases the likelihood by 0.2 percentage points. However, when all clinical and functional complications are considered, it is no longer significant. Conversely, for women, diabetes never emerges as a determinant factor of the measured outcome. Our results somehow contradict those obtained by Tunceli *et al.* (2005) and Minor and MacEwan (2016). The former authors concluded that diabetes significantly reduced the probability of being employed for US men and women, being less likely to have a job by 7.1% and 4.4%, respectively. The difference in the results might be due to the inclusion of healthy lifestyles variables and complications in the present study, as Tunceli *et al.* (2005) only controlled for number of chronic diseases, or the sample composition, since their analysis focused on people aged 51 to 61 years old. With respect to the work by Minor and MacEwan (2016), their results show a decrease in both female and male employment rates by 19 and 11 percentage points when diabetes was diagnosed and 12 and 8, respectively, in case of undiagnosed diabetes. In this case, differences might be due to the fact that the authors only included diabetes as a health variable. On the other hand, Seuring *et al.* (2015) reported that diabetes reduced the likelihood of being employed by 10% and 4.2% in men and women, respectively. Nevertheless, when they included the family history of diabetes as an instrumental variable, diabetes was no longer a determinant factor of working status.

<H4>4.1.1.2 By age

When the sample is divided into age groups (Table S4, Appendix), diabetes is a determinant factor of unemployment in later ages, from 41 years old and older, although its interpretation changes between ages. Diabetes is always significant and positively related with the probability of being unemployed in those aged 41 to 60 years old, regardless of the covariates included, and significant and negatively associated with unemployment only when all clinical and functional complications are considered in the subsample aged above 60 years old. For those aged 41 – 50 years old, the risk of being unemployed rises by 5 percentage points for those with diabetes in

Model A and by 3.9 percentage points after controlling for every complication, Model D. In case of the individuals aged 51 – 60 years old, diabetes increases the risk of being unemployed by 0.9 percentage points in Model A and by 1.2 percentage points after controlling for all clinical and functional complications, Model D. Contrariwise, diabetes reduces the likelihood of unemployment by 2.1 percentage points for those in the later ages, above 60 years old<xps:span class="xps_endnote">4</xps:span>. Thus, the effect of diabetes has been confirmed in previous studies (Seuring *et al.*, 2015), concluding that diabetes reduces the probability of being employed only in later ages.

The significant role of diabetes as a determinant of unemployment in later ages might be driven by the type of diabetes that these group of people are more likely to suffer from, diabetes type II. As it has already been mentioned, the rise in the prevalence of diabetes will be led by diabetes type II (O'Shea *et al.*, 2013), which is particularly prevalent in old adults (Sloan *et al.*, 2008). Moreover, diabetes type II impairs productivity in several ways: forcing early retirement (Norlund *et al.*, 2001; Herquelot *et al.*, 2011; Rumball-Smith *et al.*, 2014), increasing absenteeism (Tunceli *et al.,* 2005; Hex *et al.,* 2012) or decreasing productivity at work (Hex *et al.*, 2012; American Diabetes Association, 2013).

<H3>4.1.2 Diabetes and duration of unemployment

Most of the studies that have been reviewed have analyzed the number of lost workdays due to diabetes. Given that such kind of information is missing in our data, we provide evidence on the association between suffering from diabetes and the duration of unemployment.

The average marginal effects from the ordered probit regression on duration of unemployment are reported in Table 3. Average marginal effects come from Model D (clinical and functional complications included) for the different income intervals that have been considered in the study. Diabetes is significant and negatively related to short-term unemployment (less than one year) and significant and positively associated with long-term (one year or more). That is, people with diabetes are 0.9 percentage points and 8.4 percentage points more likely to unemployment lasting between 1 to 2 years and more than two years, respectively, compared to those without diabetes. Literature has not often looked at the duration of working status, measuring most of them the number of days lost due to health. However, Vijan *et al.* (2004) did analyze the duration of three working status: disabled, early-retired and not working due to health disability. Although the outcomes are not the same as the one we use, they did report that there were no significant differences between those with and without diabetes with respect to its association with duration of disability and early-retirement, which is actually opposite to what we find: differences do exist in length of unemployment between people with diabetes and their counterparts.

<H2>4.2 <u>Diabetes and income</u>

Table 4 shows the average marginal effects from the ordered probit regression models applied on earnings. Table 4 reports the average marginal effects from Model D (clinical and functional complications included) for the different income intervals that have been considered in the study. Diabetes significantly increases the probability of lower income and reduces the likelihood of having higher earnings. For example, having income lower than 550€ is 0.8 percentage points more likely among those with diabetes, but suffering from diabetes reduces the probability of having earnings between 2701 and 3450€ by 1.5 percentage points. Within socio demographic factors, greater age is the only one which is significant and positively associated with higher income.

Our results confirm the burden of diabetes on income and earnings, which has already widely studied in the literature. Most of the studies conclude that those who have diabetes suffer from decrements in their earnings (Mayfield *et al.*, 1999; Valdmanis *et al.*, 2001; Plaveev *et al.*, 2006; Schofield *et al.*, 2014; Schofield *et al.*, 2015), although some have reported that diabetes has no significant effect on wages (Seuring *et al.*, 2016), which would be contradicted by our findings.

<H3>4.2.1 Subgroup analysis

<H4>4.2.1.1 By gender

Tables S4 and S5 included in the Appendix show the average marginal effects from the ordered probit regression (Model D) on monthly household income for females and males, respectively. Diabetes stands as a significant predictor of household income only for males. As it happens in the whole sample, diabetes increases the likelihood of having lower income, whereas it reduces the probability of receiving high earnings per month. For instance, diabetes increases the probability of having less than 550€ per month as income by 1.7 percentage points. Also, the likelihood of having greater income than 2700€ per month is reduced by 3.1 percentage points in case people have diabetes.

The differences with regards to the effect of diabetes on income depending on gender was, nevertheless, neglected in a recent study (Seuring *et al.*, 2016), concluding that diabetes had no significant impact on wages, regardless of gender. However, another study contradicts our results. Minor (2013) reported that diabetes had a significant effect on wages only in women and in case of type I, even after including comorbidities as we do. Moreover, Minor also showed that greater length of diabetes type II diagnosis led to significant decreases in female wages, but not for men. The differences in the results could be due to their possibility to distinguish between diabetes types and have information about the time since diagnosis. Finally, Chu *et al.* (2001) showed that earnings loss due to diabetes and diabetes-complications were greater for US men than for females, regardless of their ethnicity and age. Although the outcome is different from the one we use, we could conclude that diabetes burden on earnings is greater for men, compared to their counterparts.

<H4>4.2.1.2 By age

When the sample is divided into age groups (Tables S6-S10, Appendix), diabetes stands as a significant predictor of household income only for those aged 41 to 50 years old. As it happens in the whole sample and for men, diabetes is positively associated with lower income and negatively related to higher monthly earnings. Diabetes increases the probability of having less than 550€ per month as income by 2.4 percentage points. Also, the likelihood of achieving a monthly income between 2700€ and 3450€ is reduced by 4.8 percentage points in case people have diabetes.

Our findings somehow support those obtained by another study concluding that only in case time since diagnosis of diabetes was greater than 20 years, so older people, wages were reduced (Seuring *et al.*, 2016). The significant role of diabetes as a determinant of (lower) household income only in advanced age could be the result of the diabetes type that these people are more likely to suffer from, diabetes type II. Previous studies have already analyzed that the productivity loss costs of diabetes type II are much higher than those generated by diabetes type I (Hex *et al.*, 2012; Minor, 2013).

<H1>5 Conclusion

This paper contains empirical evidence on the effect that diabetes has on employment status and wages, enhancing the existing literature by analyzing also the duration of unemployment, if applicable, and by controlling for diabetes-related complications, both clinical and functional. We found that having diabetes is not significantly associated with the probability of being unemployed. However, diabetes is always significant and negatively associated with long-term unemployment and income, regardless of the variables included in the regression analyses. Such different association between diabetes and the outcomes could be due to the fact that those who have diabetes could be discriminated by their employers, being allocated into lower-skills demanding types of job (Songer *et al.*, 1989), which are usually associated with lower wages, leading to reduced income, but still being employed. On the other hand, once people with diabetes are unemployed, if employers are concerned about the lower productivity of people with diabetes (Hex *et al.*, 2012), they will be more likely to hire new healthy employees than workers who have diabetes, increasing the length of their unemployment status. Nevertheless, more research will be needed to confirm and further investigate these findings as well as their interpretation.

In addition, the present study showed that changes in labor outcomes and employment patterns were strongly influenced by the characteristics of individuals. Thus, there were mixed reactions to this econometric approach, depending on the age and gender, among other factors. It was only for men to whom diabetes increased the probability of being unemployed and a determinant factor in those individuals aged 41 and above. Same subgroups reported significant association for diabetes and our second outcome, household income, increasing the probability of lower income if men had diabetes, as well as in case of individuals aged 41 to 50 years old. The greater burden of diabetes in later ages and in men (O'Shea *et al.*, 2013) could be due to the type of diabetes that they suffer from, diabetes type II. Despite the fact that it was not possible to distinguish diabetes types in our dataset, we do find a significant effect of diabetes in advancing aged, in whom the most prevalent type of diabetes is diabetes type II (Sloan *et al.*, 2008), which is a more disabling condition (Murray *et al.*, 2010).

We improve the existing literature by confirming the key role that clinical and functional complications play when evaluating the impact of diabetes, providing additional explications to the differences between subgroups others than the family history of diabetes (Minor and MacEwan, 2016). Our findings also suggest that diabetes is an essential determinant of lower income and long-term unemployment, contradicting previous authors, who suggested that diabetes has no significant impact on wages (Seuring *et al.*, 2016) and duration of labor outcomes (Vijan *et al.*, 2004)

Several implications can be derived from the above findings. First, there seems to be a considerable gap in the duration of unemployment and income between those reporting suffering from diabetes and those who do not. Second, differences in the impact of diabetes with regards to comorbidity and functional complications should be widely analyzed. It has been previously mentioned that comorbidity increases substantially the cost of diabetes (Norlund *et al.*, 2001) and our results confirm this idea since we provide evidence about the mediating role that clinical and functional complications play. Third, special attention should be paid to people in advancing age, as diabetes is a disease highly prevalent in old people and it has been proved by our results that increases in unemployment in people with diabetes are present after aged of forty years old, confirming the results reported by previous authors (Seuring *et al.*, 2015).

All in all, our findings allow policy makers to develop better intervention programs to improve health. In light of empirical implications, it may be helpful driving interventions programs towards diabetes prevention and its management, since diabetes is not a disease that impairs health itself, but through its complications. So, delaying the onset of diabetes would also delay the onset of its complications and a better management of the disease might decrease its burden on daily activities and work performance.

By focusing on diabetes problems, we are not trying to divert attention away from other important challenges. But rather because enhancing health capital can stimulate economic growth and citizens' well-being, thereby reducing unemployment and social inequality. Consistent with this, understanding why things are going wrong helps to identify how to place them right.

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</BIBL>

FIGURES

<Figure>Figure 1: Proportion of people unemployed by household income and diabetes status

<Figure>Figure 2: Average probability of being unemployed by diabetes status, age and gender

<Table>TABLE 1: Definitions of Variables and Summary Statistics

Variables		**Definition**	**Whole sample (N = 36,087)**	**People with diabetes (N = 1,710)**	**People without diabetes (N = 34,377)**	**T-test of mean difference**
			Mean ± (SD)	**Mean ± (SD)**	**Mean ± (SD)**	**p-value**
Labor status	*Unemployed*	1 if unemployed	0.21	0.20	0.21	0.132
	Unem_6	1 if unemployed for 6 months or less	0.05	0.02	0.05	0.000***
	Unem_6_12	1 if unemployed for 6 months to 1 year	0.03	0.01	0.03	0.000***
	Unem_12_24	1 if unemployed for 1 to 2 years	0.03	0.03	0.03	0.918
	Unem_24	1 if unemployed for more than 2 years	0.06	0.06	0.06	0.174
Age	*Age*	Age (in years)	42.44 ± (12.22)	53.29 ± (9.72)	41.99 ± (12.17)	0.000***
Gender	*Female*	1 if female	0.50	0.43	0.51	0.000***
Education and Marital Status	*Educ1*	1 if primary education or below (reference category)	0.17	0.29	0.16	0.000***
	Educ2	1 if compulsory secondary education	0.32	0.37	0.31	0.000***
	Educ3	1 if non-compulsory and pre-university secondary education	0.11	0.09	0.11	0.005***

	Educ4	1 if specific labor training	0.14	0.11	0.15	0.000***
	Educ5	1 if university graduate	0.14	0.09	0.14	0.000***
	Married	1 if married	0.63	0.77	0.62	0.000***
Household income	*Hhinc_550*	1 if household income per month less than 550€ (reference category)	0.04	0.04	0.04	0.106
	Hhinc_551_800	1 if household income per month 551 to 800€	0.09	0.10	0.09	0.074*
	Hhinc_801_1050	1 if household income per month 801 to 1050€	0.10	0.11	0.10	0.022**
	Hhinc_1051_1300	1 if household income per month 1051 to 1300€	0.11	0.09	0.11	0.019**
	Hhinc_1301_1550	1 if household income per month 1301 to 1550€	0.07	0.08	0.07	0.495
	Hhinc_1551_1850	1 if household income per month 1551 to 1850€	0.07	0.07	0.07	0.802
	Hhinc_1851_2250	1 if household income per month 1851 to 2250€	0.09	0.08	0.09	0.573
	Hhinc_2251_2700	1 if household income per month 2251 to 2700€	0.16	0.15	0.16	0.213
	Hhinc_2701_3450	1 if household income per month 2701 to 3450€	0.21	0.20	0.21	0.464
Lifestyle factors	*Overweight*	1 if respondent has overweight (25 kg/m2 ≤ BMI < 30 kg/m2)	0.36	0.41	0.36	0.000***
	Obesity	1 if respondent is obese (BMI ≥ 30 kg/m2)	0.15	0.41	0.14	0.000***
	Current smoker	1 if respondent currently smokes	0.33	0.28	0.33	0.000***
	Ever smoke	1 if respondent has ever smoked, but does no longer do	0.21	0.29	0.20	0.000***
Health	*Diabetes*	1 if respondent has diabetes	0.05	-	-	-
	Diabetes_last12 months	1 if diabetes has been diagnosed in the last 12 months	-	0.93	-	-

	Hypertension	1 if respondent has high blood pressure	0.16	0.48	0.14	0.000***
	Heart attack	1 if respondent has ever had a heart attack	0.01	0.06	0.01	0.000***
	Arthritis	1 if respondent has arthritis	0.13	0.32	0.12	0.000***
	Back pain	1 if respondent has back pain	0.27	0.40	0.27	0.000***
	Asthma	1 if respondent has asthma	0.05	0.06	0.05	0.947
	Chronic lung disease	1 if respondent suffers from chronic lung disease	0.03	0.10	0.03	0.000***
	Ulcer	1 if respondent has gastric ulcer	0.04	0.07	0.04	0.000***
	Cholesterol	1 if respondent has cholesterol	0.16	0.46	0.15	0.000***
	Stroke	1 if respondent has ever had a stroke	0.01	0.02	0.01	0.000***
	Cancer	1 if respondent has cancer	0.02	0.04	0.02	0.000***
	Limitations in Activities of Daily Living (ADL)	Limitation in performing ADL due to health, from 0 (no limitations) to 2 (severely limited)	0.18 ± (0.43)	0.40 ± (0.60)	0.16 ± (0.42)	0.000***

Note: Sample of respondents aged 18-65. *** p<0.01, ** p<0.05, * p<0.1

<Table>TABLE 2: Average marginal effects of probit model for being unemployed

VARIABLES	Average Marginal Effects Model A	Average Marginal Effects Model B	Average Marginal Effects Model C	Average Marginal Effects Model D
Diabetes	-0.004	-0.006	-0.008	-0.009
	(0.010)	(0.010)	(0.011)	(0.011)
Age	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.008*	-0.006	-0.005	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Educ2	0.043***	0.044***	0.043***	0.044***
	(0.005)	(0.005)	(0.005)	(0.005)
Educ3	-0.048***	-0.047***	-0.047***	-0.047***
	(0.008)	(0.008)	(0.008)	(0.008)
Educ4	-0.012*	-0.011	-0.011	-0.010
	(0.007)	(0.007)	(0.007)	(0.007)
Educ5	-0.069***	-0.068***	-0.068***	-0.067***
	(0.007)	(0.007)	(0.007)	(0.007)
Married	-0.040***	-0.040***	-0.040***	-0.039***

	(0.005)	(0.005)	(0.005)	(0.005)
Overweight	0.016***	0.016***	0.015***	0.016***
	(0.005)	(0.005)	(0.005)	(0.005)
Obesity	0.046***	0.046***	0.043***	0.043***
	(0.006)	(0.006)	(0.007)	(0.007)
Current smoker	0.065***	0.063***	0.063***	0.063***
	(0.005)	(0.005)	(0.005)	(0.005)
Ever smoke	0.019***	0.017***	0.017***	0.017***
	(0.006)	(0.006)	(0.006)	(0.006)
Arthritis		-0.022***	-0.022***	-0.026***
		(0.007)	(0.007)	(0.007)
Back pain		0.006	0.005	0.003
		(0.005)	(0.005)	(0.005)
Asthma		0.013	0.013	0.012
		(0.009)	(0.009)	(0.009)
Chronic lung disease		0.043***	0.042***	0.040***
		(0.012)	(0.012)	(0.012)
Ulcer		0.065***	0.064***	0.063***
		(0.011)	(0.011)	(0.011)
Hypertension			0.015**	0.014**
			(0.006)	(0.006)
Heart attack			0.027	0.025
			(0.021)	(0.021)
Cholesterol			-0.008	-0.008
			(0.006)	(0.006)
Stroke			-0.025	-0.033
			(0.030)	(0.030)
Cancer			-0.004	-0.009
			(0.015)	(0.015)
Limitation in activities of daily living				0.017***
				(0.005)
Observations	36,087	36,087	36,087	36,087

Data are partial derivatives of probability (marginal effects with SE in parentheses) with respect to independent variables. The derivatives are computed as the difference in probabilities as the dummy variable takes on the values 0 and 1, with the other variables at the sample means.
All models include the following covariates: diabetes, age and age squared, gender, education, marital status and lifestyle factors (overweight, obesity, currently smoking and ever smoke). Model B adds to the previous model diabetes non-related clinical complications: arthritis, back pain, asthma, chronic lung disease and gastric ulcer. Model 3 includes the above variables and diabetes-related clinical variables: hypertension, heart attack, cholesterol, stroke and cancer. Model 4 adds the dummy variable on having any limitation in performing ADLs.
*** p<0.01, ** p<0.05, * p<0.1

<Table>TABLE 3: Average marginal effects (AME) of Model D ordered probit model for unemployment length

VARIABLES	AME Model D: less than 6 months	AME Model D: 6 months - 1 years	AME Model D: 1 - 2 years	AME Model D: more than 2 years
Diabetes	-0.062***	-0.007***	0.009***	0.084***

	(0.020)	(0.002)	(0.003)	(0.027)
Age	-0.007***	-0.001***	0.001***	0.010***
	(0.000)	(0.000)	(0.000)	(0.001)
Female	-0.025***	-0.003***	0.004***	0.034***
	(0.008)	(0.001)	(0.001)	(0.010)
Educ2	0.015*	0.002*	-0.002*	-0.021*
	(0.008)	(0.001)	(0.001)	(0.011)
Educ3	0.029**	0.003**	-0.004**	-0.039**
	(0.014)	(0.002)	(0.002)	(0.019)
Educ4	0.034***	0.004***	-0.005***	-0.046***
	(0.012)	(0.001)	(0.002)	(0.016)
Educ5	0.069***	0.008***	-0.010***	-0.093***
	(0.013)	(0.002)	(0.002)	(0.018)
Married	0.015*	0.002*	-0.002*	-0.020*
	(0.008)	(0.001)	(0.001)	(0.011)
Overweight	0.014*	0.002*	-0.002*	-0.019*
	(0.008)	(0.001)	(0.001)	(0.011)
Obesity	0.026**	0.003**	-0.004**	-0.035**
	(0.010)	(0.001)	(0.002)	(0.014)
Current smoker	-0.031***	-0.003***	0.004***	0.041***
	(0.008)	(0.001)	(0.001)	(0.011)
Ever smoke	0.008	0.001	-0.001	-0.010
	(0.010)	(0.001)	(0.001)	(0.014)
Arthritis	0.011	0.001	-0.002	-0.015
	(0.014)	(0.001)	(0.002)	(0.018)
Back pain	0.002	0.000	-0.000	-0.002
	(0.009)	(0.001)	(0.001)	(0.012)
Asthma	-0.052***	-0.006***	0.008***	0.071***
	(0.015)	(0.002)	(0.002)	(0.021)
Chronic lung disease	-0.036*	-0.004*	0.005*	0.049*
	(0.019)	(0.002)	(0.003)	(0.026)
Ulcer	-0.095***	-0.010***	0.014***	0.128***
	(0.018)	(0.002)	(0.003)	(0.023)
Hypertension	-0.005	-0.001	0.001	0.007
	(0.011)	(0.001)	(0.002)	(0.015)
Heart attack	-0.076**	-0.008*	0.011*	0.102**
	(0.039)	(0.004)	(0.006)	(0.052)
Cholesterol	0.007	0.001	-0.001	-0.010
	(0.011)	(0.001)	(0.002)	(0.015)
Stroke	0.096*	0.011*	-0.014*	-0.129*
	(0.051)	(0.006)	(0.008)	(0.069)
Cancer	0.026	0.003	-0.004	-0.035
	(0.029)	(0.003)	(0.004)	(0.039)
Limitation in activities of daily living	-0.026***	-0.003***	0.004***	0.035***
	(0.009)	(0.001)	(0.001)	(0.012)
Observations	7,592	7,592	7,592	7,592

Data are partial derivatives of probability (marginal effects with SE in parentheses) with respect to independent variables. The derivatives are computed as the difference in probabilities as the dummy variable takes on the values 0 and 1, with the other variables at the sample means. Only those unemployed individuals answered to the question about the time being unemployed.

All models include the following covariates: diabetes, age and age squared, gender, education, marital status and lifestyle factors (overweight, obesity, currently smoking and ever smoke). Model B adds to the previous model diabetes non-related clinical complications: arthritis, back pain, asthma, chronic lung disease and gastric ulcer. Model 3 includes the above variables and diabetes-related clinical variables: hypertension, heart attack, cholesterol, stroke and cancer. Model 4 adds the dummy variable on having any limitation in performing ADLs.
*** p<0.01, ** p<0.05, * p<0.1

<Table>TABLE 4: Average marginal effects (AME) of ordered probit model for household income

VARIABLES	AME Model D: less than 550€	AME Model D: 551-800€	AME Model D: 801-1050€	AME Model D: 1051-1300€
Diabetes	0.008*	0.005*	0.004*	0.003*
	(0.004)	(0.003)	(0.002)	(0.001)
Age	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.002	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Educ2	0.002	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Educ3	-0.001	-0.001	-0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.001)
Educ4	0.003	0.002	0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Educ5	0.003	0.002	0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Married	0.003	0.002	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Overweight	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Obesity	0.002	0.001	0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Current smoker	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Ever smoke	0.003	0.002	0.002	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Arthritis	0.005*	0.003*	0.002*	0.002*
	(0.003)	(0.002)	(0.001)	(0.001)
Back pain	0.006***	0.004***	0.003***	0.002***
	(0.002)	(0.001)	(0.001)	(0.001)
Asthma	0.000	0.000	0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.001)
Chronic lung disease	0.005	0.003	0.003	0.002
	(0.005)	(0.003)	(0.003)	(0.002)
Ulcer	0.008*	0.005*	0.004*	0.002*
	(0.005)	(0.003)	(0.002)	(0.001)
Hypertension	0.007**	0.004**	0.003**	0.002**
	(0.003)	(0.002)	(0.001)	(0.001)
Heart attack	-0.006	-0.004	-0.003	-0.002

	(0.009)	(0.006)	(0.004)	(0.003)
Cholesterol	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Stroke	-0.002	-0.001	-0.001	-0.001
	(0.011)	(0.008)	(0.006)	(0.004)
Cancer	0.003	0.002	0.001	0.001
	(0.006)	(0.004)	(0.003)	(0.002)
Limitation in activities of daily living	0.001	0.001	0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	36,087	36,087	36,087	36,087

Data are partial derivatives of probability (marginal effects with SE in parentheses) with respect to independent variables. The derivatives are computed as the difference in probabilities as the dummy variable takes on the values 0 and 1, with the other variables at the sample means.
All models include the following covariates: diabetes, age and age squared, gender, education, marital status and lifestyle factors (overweight, obesity, currently smoking and ever smoke). Model B adds to the previous model diabetes non-related clinical complications: arthritis, back pain, asthma, chronic lung disease and gastric ulcer. Model 3 includes the above variables and diabetes-related clinical variables: hypertension, heart attack, cholesterol, stroke and cancer. Model 4 adds the dummy variable on having any limitation in performing ADLs.
*** p<0.01, ** p<0.05, * p<0.1

<Table>TABLE 4: (continued)

VARIABLES	AME Model D: 1301-1550€	AME Model D: 1551-1850€	AME Model D: 1851-2250€	AME Model D: 2251-2700€	AME Model D: 2701-3450€
Diabetes	0.001*	0.000	-0.001*	-0.005*	-0.015*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.008)
Age	-0.000***	-0.000**	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.000	-0.000	0.000	0.001	0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)
Educ2	0.000	0.000	-0.000	-0.001	-0.003
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Educ3	-0.000	-0.000	0.000	0.001	0.003
	(0.000)	(0.000)	(0.000)	(0.002)	(0.006)
Educ4	0.000	0.000	-0.000	-0.001	-0.005
	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)
Educ5	0.000	0.000	-0.000	-0.002	-0.006
	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)
Married	0.000	0.000	-0.000	-0.002	-0.006
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Overweight	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Obesity	0.000	0.000	-0.000	-0.001	-0.004
	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)
Current smoker	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Ever smoke	0.000	0.000	-0.000	-0.002	-0.006
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)

Arthritis	0.000*	0.000	-0.001*	-0.003*	-0.009*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)
Back pain	0.001***	0.000*	-0.001***	-0.004***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Asthma	0.000	0.000	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.002)	(0.007)
Chronic lung disease	0.001	0.000	-0.001	-0.003	-0.010
	(0.000)	(0.000)	(0.001)	(0.003)	(0.010)
Ulcer	0.001*	0.000	-0.001*	-0.004*	-0.015*
	(0.000)	(0.000)	(0.000)	(0.003)	(0.009)
Hypertension	0.001**	0.000	-0.001**	-0.004**	-0.013**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)
Heart attack	-0.001	-0.000	0.001	0.003	0.011
	(0.001)	(0.000)	(0.001)	(0.005)	(0.017)
Cholesterol	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
Stroke	-0.000	-0.000	0.000	0.001	0.004
	(0.001)	(0.000)	(0.001)	(0.007)	(0.022)
Cancer	0.000	0.000	-0.000	-0.002	-0.005
	(0.001)	(0.000)	(0.001)	(0.003)	(0.011)
Limitation in activities of daily living	0.000	0.000	-0.000	-0.001	-0.002
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Observations	36,087	36,087	36,087	36,087	36,087

Data are partial derivatives of probability (marginal effects with SE in parentheses) with respect to independent variables. The derivatives are computed as the difference in probabilities as the dummy variable takes on the values 0 and 1, with the other variables at the sample means.
All models include the following covariates: diabetes, age and age squared, gender, education, marital status and lifestyle factors (overweight, obesity, currently smoking and ever smoke). Model B adds to the previous model diabetes non-related clinical complications: arthritis, back pain, asthma, chronic lung disease and gastric ulcer. Model 3 includes the above variables and diabetes-related clinical variables: hypertension, heart attack, cholesterol, stroke and cancer. Model 4 adds the dummy variable on having any limitation in performing ADLs.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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<en><xps:span class="xps_label">1</xps:span>By way of illustration, survey data for the intervening years 2007-2010 are unavailable in Spain and the 2011-2012 survey responders are not the same as the previous surveys.

<en><xps:span class="xps_label">2</xps:span>Non-Spanish people have been dropped from the analysis, given their high diabetes incidence rate.

<en><xps:span class="xps_label">3</xps:span>We also estimate eq. (5) as logit regression and, after looking at the Akaike's (AIC) and Schwarz's Bayesian (BIC) information criteria, probit models are the ones that better-fit our data (Table S2, Appendix), given their smaller AIC and BIC coefficients.

<en><xps:span class="xps_label">4</xps:span>This somewhat counterintuitive result may be a result of job lock in this population group since they might be motivated to stay with a particular employer, given the proximity to retirement and the uncertainty of the job market due to the Great Recession.