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Effects of Type I Diabetes on Labor Force Participation: A Propensity Score Match

Ore Aina-Badejo
CUNY Hunter College

Effects of Type I Diabetes on Labor Force Participation

by Ore Aina-Badejo

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Date: November 20, 2018	Signature of first Reader: Partha Deb
Date: November 20, 2018	Signature of Second Reader: Temisan Agbeyegbe

Abstract:

Type I Diabetes (T1D) is a chronic autoimmune mediated form of insulin resistance that has lasting socioeconomic effects from childhood through old age that may impact labor force participation. Examining this relationship will enhance our understanding of life-long chronic illness beyond individual medical/financial impact by establishing broader socioeconomic implications. This study utilized data from the 2008-2015 data set of the Medical Expenditure Panel Survey (MEPS), to explore the effects of T1D on labor force participation. It was hypothesized that having T1D would decrease both employability and contribution to the labor force. Utilizing methods of propensity score matching and entropy balancing, the hypothesis was shown to be correct, with T1D having an overall negative effect on labor force participation in regards to employability and number of sick days taken. This study highlights the need for further insight into the individual factors of those with T1D that lend to a decreased participation in the labor force.

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I. Introduction

Type I diabetes mellitus (T1D) is a chronic autoimmune mediated form of insulin deficiency defined by the progressive self-destruction of pancreatic insulin producing β-cells (Cnop et al., 2005; Saberzadeh-Ardestani et al., 2018; Williams & Farrar, 1986). With no known cause and no curative treatment, those affected with the illness require a constant supply of an exogenous insulin analogue throughout their lifetime in order to maintain normal levels of blood glucose which are otherwise lethal (Katsarou et al., 2017). Despite tediously calculated insulin dosing with an exogenous insulin analogue based on method of administration, weight, food intake, exercise and metabolic basal rate, maintaining constant levels of normoglycemia is extremely difficult. As a result, most individuals affected with this immune mediated illness end up developing life-threatening diabetic related complications including cardiovascular (heart disease, stroke, cardiomyopathy) and microvascular (retinopathy, neuropathy, kidney disease) (López-Bastida et al., 2017).

Type II diabetes (T2D), on the other hand, is an insulin independent metabolic mediated form of diabetes which is usually developed in older adulthood due to insulin resistance. The typical treatment regimen for T2D is significantly less demanding and usually consists of an insulin resistance lowering drug, with more severe cases requiring a daily dose of an insulin analogue. Additionally, the rate of hospitalization and life-threatening episodes of diabetic related events such as hypoglycemia and diabetic ketoacidosis is disproportionately higher for T1D's. With obesity at an all-time high in the United States(Ortega & Lavie, 2018), the prevalence of Type II diabetes, despite its

prevention with healthy diet and exercise, far exceeds that of Type I diabetes(National Institute of Diabetes and Digestive Kidney Diseases, 2017).. As a result, the vast majority of socioeconomic studies looking at the impact of diabetes on productivity and overall economic well-being have been mainly conducted on either "diabetics" as a whole or focusing solely on those with T2D. One major reason as to why this lack of distinction is problematic lies in the duration of each disease. T1D is a life-long chronic illness that begins during childhood, therefore productivity of these individuals is impacted over decades and spans into adulthood.

A lack of metabolic control and diabetic complications in children with T1D has been found to negatively affect school attendance and performance (Nielsen, Ovesen, Mortensen, Lau, & Joensen, 2016a). Additionally, parents reportedly have to take more time off of work and spend extra money on resources caring for their child (i.e. monitoring systems, home education, private childcare, medication, etc.)(Tao et al., 2010). This lends itself to downstream consequences resulting in a lack of success in the labor market since "school-leavers with few or no qualifications are at a greater risk of unemployment throughout adulthood." Contribution to the labor market and society would likely have been established in those with T1D, as opposed to those with T2D who develop the illness by the time they are already established members of the labor market.

According the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK), an estimated 30.3 million American are affected with diabetes, with only 1.5 million of those individuals having T1D. Accordingly, T1D only accounts for approximately 5% of all individuals affected with diabetes in the Unites States (Roberts & Smith, 2018). Despite the significantly lower population of affected individuals, the

average annual cost of illness (COI) per case of T1D is reportedly $14,856, in comparison to $9,677 for T2D (Dall et al., 2010). Currently, epidemiological and socioeconomic studies done in the United States rarely distinguish between these two pathophsyiologically different forms of diabetes. Additionally, this life-long illness, typically diagnosed during early adolescence, is often left ignored when studying the impact on labor force participation in society.

Current research and data on the effects of T1D, specifically, on education, occupational status and overall contribution to society is extremely limited. Based on a thorough literature search, the majority of published studies explore very limited data from non-US countries, with most including all forms of diabetes in their analysis (Brod, Christensen, Thomsen, & Bushnell, 2011; Federation, n.d.; Geelhoed-Duijvestijn et al., 2013; López-Bastida et al., 2017; Nielsen, Ovesen, Mortensen, Lau, & Joensen, 2016b; Steen Carlsson et al., 2010). The aim of this study is to demonstrate the effects of T1D on United States labor force participation and productivity (measured as income in this paper).

II. Literature Review

As previously mentioned, prior research focusing on the impact of T1D on the labor market is mainly limited to countries outside of the United States. The majority of literature utilizes data from either Sweden and Finland, two countries with the highest incidence of T1D. According to the 2011 survey reported by the International Diabetes Federation's Diabetes Atlas, both Finland and Switzerland have an incidence of 57.6 and 43.1, respectively, per 100,000 children ages 0 to 14. This is in comparison to 23.7 per 100,000 cases in the United States. Although this data is international, the correlation

between disease state and labor force contribution, as well as economic modeling used to analyze this data can be extended to the methods considered for this study.

In a study published by Persson et. al in 2018, the effect of T1D on labor market outcomes in Sweden is analyzed population utilizing data from the Swedish Childhood Diabetes Register (SCDR) of those born between 1962 and 1979(Persson, Dahlquist, Gerdtham, & Steen Carlsson, 2018). The SCDR is a database of children diagnosed with T1D under the age of 15, used to study long term consequences of T1D and its complications. The database is linked to a number of Swedish governmental databases with data matched to each person via a Swedish personal identification number. For example, data was linked from the SCDR to the Longitudinal Integration Database for Health Insurance and Labor Market Studies (LISA), as well as the National Board of Health and Welfare. Correlation between T1D on employment and earning were assed with the use of four mediating variables—adult health, education, occupation and family formation while controlling for both demographic and socioeconomic background.

The Sobel-Goodman mediation test was utilized to assess the effects of each variable on employment and earning of T1D vs healthy controls. Statistical analysis showed that childhood-onset T1D negatively impacted employment with an odd's ratio of 0.68 (95% CI) as well as earnings with an odds ratio of 0.76 (95% CI). Absenteeism from work was reported to contribute to over 50% of negative effects on earning potential of individuals with T1D. Additionally, it was found that occupation was selected based on work place flexibility with sick time for diabetes care related events. This lends itself to the importance of my study, exploring the effects of T1D on labor participation.

An additional case-controlled study conducted in1989 by Thomas J. Songer, et al, explored the consequences of T1D on employment outlook in the United States (Songer et al., 1989). Using a cohort of 158 T1D's and 158 healthy control siblings, the "employability" of each T1D individual relative to their paired healthy control was assessed. Individuals with T1D reported a higher rate of job refusal (56% vs. 42%, p = .02, n = 151 pairs, odds ratio 1.75, 95% Cl 1.07,2.92) as well as a lower rate of full time employment, (67.3% vs. 84.6%; P < .01). Decrease in full time employment was attributed to work disability (due to diabetic related complications) which was reportedly 7 times greater relative to the healthy patient-matched control. The study also suggested hiring discrimination towards those with T1D due to a perceived inability to maintain good job attendance record.

Additional studies focusing on labor market experience of individuals with T1D in Sweden and Norway, found that those with T1D were less likely to be employed in comparison to non-T1D individuals as well as the general population. Job refusal and discrimination studies of those with diabetes (undistinguished) were found to have an increased absenteeism (Milton, Holland, & Whitehead, 2006). Such studies are lacking in the United States. Studies that have been found only reference the diabetic population as a whole, without distinction for T1D. Therefore, the results may not truly represent the employment experience of the T1D community.

In the study published by Betty Tao et. Al in 2010, the cost of type 1 diabetes in the U.S. was estimated by using a nationally representative data set which includes data from National Health and Nutrition Examination Survey (NHANES) matched with data from the MEPS, where they identified T1D patients by applying the "clinically-derived

definition"; using age of onset, body mass index and usage of insulin therapy. Most other studies defined diabetes by asking whether a participant has ever been told by a physician that they have diabetes. They noticed an exception with NHANES which goes further by administering a C-peptide test for T1D. Tao et. al noticed that this method of identification led to a very small population of T1D patients and this is why they used the clinically derived method above by refined their population by eliminating children under 18 diagnosed with diabetes who are also considered obese with this they had accounted for overestimation or underestimation of their population. To ensure that T1D was the only differing variable for their population they adopted a form of matching called propensity score matching, which is basically a way of creating a control group where there is only one thing separating the two groups (in this case the presence of T1D). To do this they included a slew of relevant covariates to determine the nondiabetic diabetic-type sample. They chose variables that were independent of whether or not the individual has T1D, after conditioning for all the matching covariates to ensure that having T1D is the only difference between a T1D patient and their matched counterpart that would affect the outcome.

The authors used a logit specification to achieve the T1D propensity score and applied one to one matching with replacement, to test the sensitivity of their matching they used kernel density matching which will use all the nondiabetics for comparison but weighed their importance by the propensity score. They didn't find any difference in their results from their main analysis, they then calculated their standard error by bootstrapping with 500 iterations and reported a 95 percent confidence interval for all their results. Their suitable covariates for matching were age, female, Metropolitan

statistical area (MSA), Nonwhite, Region, Year, Birth weight, Height, U.S. Citizen, In U.S. < 15 years, Eczema, Arthritis, Cancer, Mom finished HS and Dad finished HS. We would be adopting their matching method by using the same covariates that exist in our dataset and also generating a propensity score match with a logistical regression, we would also be using the clinically derived definition for T1D they have used in their study as this is the only way we can define T1D in our dataset, our study would also differ from theirs as they were trying to estimate the cost of the disease while we are trying to see the effect on the disease on wages and labor force participation.

Finally, in a 2013 study by Travis minor, he tried to investigate the effect of type 1 and type 2 diabetes duration on employment and wages(Travis Minor, 2011). His dataset is from the National Longitudinal Survey of Youth from 1979 and from there he determines his employment variable as either employed or unemployed and his T1D variable is defined by if the participant was diagnosed with diabetes before the age of 20 and if after T2D. He runs a logit regression to differentiate between participants being employed or not based on the various kinds of diabetes. He also runs a wage model to determine the participants logarithmic hourly wage based on the kinds of diabetes using the OLS method. His results showed that both the probability of employment and wages are negatively related to the number of years since the initial diagnosis of diabetes, he also showed that the effect of diabetes duration on the probability of employment shows to be nonlinear and peaked around the ages of 16 for females and 10 for males. He found a similar negative effect on wages is found in only diabetics that are male. He further stressed that failure to distinguish between the two types of diabetes may lead to counterintuitive results. We would be using similar definition for our employment

variable but we would be user newer data and specifically targeting type 1 diabetes in order to improve on his study.

This paper therefore serves a purpose of analyzing the effects of T1D on labor force participation using data selected from the Medical Expenditure Panel Survey using a number of criteria to distinguish those with T1D from those with T2D with a similar method of T1D definition and matching as Tao et. Al but using the same definition of employment and impressing on Travis Minor's study by only focusing on T1D.

IV. METHODOLOGY

1. DATA

In order to determine the effects of T1D on labor force participation, data from the 2008 – 2015 MEPS Full Year Consolidated files was used. The MEPS data set is derived from a large-scale survey of households and individuals living in the United States. Information collected includes demographic (i.e. age, sex, ethnicity, etc.), socioeconomic characteristics, medical records (i.e. health conditions, smoking status, medications, laboratory results, etc.), missed work days, healthcare use, costs and health insurance coverage.

Survey participants were de-identified, and a randomized study ID was assigned, as designated by the "DUPERSID" variable. Each de-identified participant was followed for a duration of two years, with each participant asked to answer a slew of questions (with 3 rounds per year). The information is self-reported and heavily detailed. 2008 was chosen as the start date for data analysis since that was the year MEPS started recording age of onset for diabetes (DIABAGED). MEPS does not distinguish between T1D and T2D, therefore, by utilizing age of onset as well as BMI, I was able to determine if an

individual had T1D or T2D. Lastly, 2015 was the most recent consolidated survey date, hence why it was used as the end point for data collection.

My T1D variable was created by using the MEPS variable "diabaged"; the inclusion criteria were limited to individuals diagnosed with "diabetes" prior to the age of 25 with a BMI lower than 30 which is similar to the method adopted by Tao et. Al.

Since I was focusing specifically on effects of T1D on labor force participation, an age guideline was used to define the workforce population. Therefore, I re-filtered the T1D population to people that fall between the ages of 25 – 50. Generally speaking, this would include individuals who are both post college and pre-retirement age. In the end, out of an initial study population of 52,213, my selection criteria yielded a total of 205 T1D's (0.39%). This seems to accurately reflect the incidence of T1D in the United States which is estimated to be about 0.3-0.6% of the population(Dall et al., 2009)..

2. REGRESSIONS

I started with a simple Ordinary Least Squares (OLS) regression (without balancing) by regressing the dependent variables on the independent variables. Dependent variables included employed, log of sick days and log of wage. The independent variables included age, age squared, income, a nonwhite dummy variable, a set of region dummy variables, a set of education dummy variables, female, marital status and a set of year dummy variables. An OLS regression was decidedly the best baseline strategy since it represents a very straightforward way to model.

To specifically identify the effects of T1D on employability, it was essential to match a T1D patient to a person without T1D. To find an exact match or as close to one as possible, I had to create a control group and a treatment group by using propensity

score matching to evaluate Treatment-effect (T-effect). Propensity score matching involves trying to match the control and treatment group as much as possible where the only difference between them can be attributed to T1D (Tao et al., 2010). This would allow me to account for differences observed between those with T1D and those without, such as having less education due to missing classes or less income from taking more sick days. Without balancing via propensity score matching, the treatment and control groups would be heterogeneous. This would also reduce the risk of imbalance that stems from the small population size associated with T1D. A similar method was employed by Tao et al who used the Rosenbaum and Rubin propensity score matching methods, including other covariates to ensure the matched control individuals were similar enough where the only difference was their T1D.

For my first propensity score matching I used a logit regression to estimate the propensity of having T1D. The following were used as independent variables; "age," "age squared," "nonwhite," "region," "cancer," "arthritis," "female," "marital status," "education" and "year." Individuals without T1D who had a high propensity to have T1D were used as a control group. I used the "teffect" command in Stata, which allowed me to estimate the average treatment effect, or the "ATE" as well as the average treatment effect on the treated called the "ATET." In this regression, the ATE would be the effects of having T1D on the average person, while the ATET would be the effect of having T1D on the people with T1D. The equation below illustrates the T-effect regression:

$$Y_i = \beta_0 + \beta_1 Type\ 1\ Diabetes_i + \beta_2 Age_i + \beta_3 Age^2{}_i + \beta_4 Non\ White_i +$$
$$\beta_5 \Sigma\ Region\ Dummies_i + \beta_6 Cancer_i + \beta_7 Arthritis_i + \beta_8 Female_i +$$
$$\beta_9 \Sigma Martital\ Status\ Dummies_i + \beta_{10} \Sigma Education\ Dummies_i + \beta_{11} \Sigma Year\ Dummies_i + \varepsilon_i$$

A second method for balancing, the entropy balance method referenced in "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies" was employed (Hainmueller, 2012). Entropy balance allows one to reweight a dataset based on a maximum entropy weighing scheme that assigns weight to individual data units so the covariate distribution in the reweighted dataset satisfies a set of moment conditions. This method also helps to balance covariate distributions in studies with binary treatments where the control group data can be reweighted to match the covariate moments in the treatment group. Instead of just selecting a control group with propensity score matching, I was able to match on the mean, standard deviation and skewness for the continuous independent variables (age and age squared). For the dummy variables I used to balance, when the command matches on the first moment, mean, the other two moments, standard deviation and skewness, are necessarily matched. This creates a synthetic control group that matches the treatment group on the treatment variables for all three moment conditions—mean, standard deviation and skewness for the specified covariates. It thereby eliminated both behavioral and environmental effects of T1D. The controls are the same as the OLS ones, and so the values I obtained were similar. The regression equation here is the same since I utilized the same selection criteria;

$$Y_i = \beta_0 + \beta_1 Type\ 1\ Diabetes_i + \beta_2 Age_i + \beta_3 Age^2{}_i + \beta_4 Non\ White_i +$$
$$\beta_5 \Sigma\ Region\ Dummies_i + \beta_6 Cancer_i + \beta_7 Arthritis_i + \beta_8 Female_i +$$
$$\beta_9 \Sigma Martital\ Status\ Dummies_i + \beta_{10} \Sigma Education\ Dummies_i + \beta_{11} \Sigma Year\ Dummies_i + \varepsilon_i$$

V. RESULTS

1. EMPLOYMENT

Based on the OLS regression as seen in Table 2, it would appear that having T1D has a negative impact on the likelihood of being employed, they are 11.5% less likely to be employed. This could be explained by those with T1D self-selecting out of the job market due to their inability to work. Alternatively, it is possible that employers would rather not hire those with T1D because of the high cost of medical care the employer might incur from paying for insurance.

In terms of demographic factors, it appears that non-whites are 3.8% less likely to be employed. Being female shows that you are 15% less likely to be employed. People with an education less than high school are 13% less likely to be employed while their college counterparts are 10% more likely to be employed. There seems to be a strong correlation between marital status and employment. Based on the OLS regression, widowed people are 7% less likely to be employed, while divorcees are 3% likely to be employed. Finally, we see that folks that were never married are 2% less likely to be employed. Lastly, In the year dummy, we can see how the employment rate increases, we see that people were 1 percentage point likely to be employed, likely due to the effect of the recovery from the recession in 2009.

Based on the t-effect regression in Table 2, we can see the average treatment effect on those without T1D, having T1D means you are 16% less likely to be employed. This is in comparison to the average treatment effects on the treated also from Table 2, showing that those with T1D are 16% less likely to be employed. The entropy balance results from Table 6 were very similar to the OLS results, showing that those with T1D

are 11.5% points less likely to be employed. Nonwhites are also shown to be 9 percentage points less likely to be employed. Having cancer and arthritis reduces your chance to employed by 9 percentage points and 22 percentage points respectively. Being female reduces your chance of being employed by 17 percentage points while having less than a high school degree reduces employment by 13 percentage points which seems surprisingly low compared to being female. Figure 1 shows the effects of age on employment opportunities for T1Ds and nondiabetics—as T1D's grow older, their employability goes down. In those without T1D, however, employability remains the same.

2. SICK DAYS

Based on the OLS regression in Table 3, those with T1D are 28 percentage points more likely to take sick days. This result is expected based on the employment regression showing that those with T1D are less likely to be employed; this may be a result of T1D's using too many sick days. Additionally, with a unit increase in age, you take 18 percentage points more sick days—this makes sense as the older people get the more likely the chance of their health failing and this leads to the use of more sick days. As expected, age squared has a negative correlation.

Non-whites were found to take less sick days than their white counterparts. Table 3 shows that non-whites take 3% points less sick days, and as mentioned earlier, this could be due to the fact that the field they are working in do not have as many sick day benefits as compared to their white counterparts. Lastly, there appears to be strong positive coefficients for the cancer and arthritis diagnosis, seemingly larger than T1D.

Study results show that cancer patients take 35 percentage points more sick days, while those with arthritis take 43 percentage points more sick days than their healthy counterparts. Women seem to take more sick days than males, with results showing they take 21% more sick days, a result that is consistent with current literature. Divorcees are shown to take 11 percentage points more sick days as opposed to their married counterparts. People with less than high school take 13 percentage points less sick days and this could be explained as not having access to the sick days in their possible field of employment.

In the t-effect regression showing the average treatment effect from Table 3, we can see that those with T1D take 18 percentage points more sick days, while the average treatment effect on the treated in Table 3 shows that T1Ds take 46% points more sick days. In the year 2013 we see that people took 6 percentage points more sick days, while in 2015 they took 19 percentage points more sick days.

Once again the entropy balance result from Table 3 shows that those with T1D take 29 percentage points more sick days than their nondiabetic counterparts. People with cancer took 36 percentage points more sick days while people with arthritis took 32 percentage points more sick days which is to be expected. Unexpectedly people took 34 percentage points more sick days in 2015. Figure 2 shows that with age, those with T1Ds take exceedingly more sick days than their nondiabetic counterparts who are predicted to take even fewer sick days as they get older.

3. INCOME

Table 4 shows no statistically significant impact on the wage of those T1D in comparison to the control group, which is quite surprising, as the expectation was to find

that T1Ds would be more risk averse at changing jobs because of the worry that the possible new manager could be less agreeable to taking so many sick days. The fear of losing a person with T1D from the work force could also have been a possible reason for the supposed belief in lower income for those with T1D. Age, on the other hand, shows a positive impact on wage. This is an expected outcome, as with increasing age comes an increase in employment stability one shows in their position, leading to expected growth and higher income. Age squared acts as expected, showing the negative effect. Nonwhites are shown to earn 3.8 percentage points less than their white counterparts. People with arthritis are seen to earn 4 percentage point less than their non-arthritis counterparts. Being female is correlated with earning 27 percentage points less than men, lining up with general consensus that women earn 75 cents to the dollar of most men. Widowed people earn 11.7 percentage points less than married people, while separated and never married people earn 16 percentage points and 14 percentage points less, respectively. People with less than a high school degree earn 40 percentage points less, while college goers earn 59 percentage points more than their counterparts with high school degrees as seen in other literature. We see that wage has an uptick as the years go by, this was explained earlier as the effect of the recovery from the recession.

Finally, we see in the entropy balancing regression from Table 4, no statistically significant effect to wages for people with T1D. We do see as expected a 11 percentage point increase to wage with one age unit increase while we see an inverse effect with age squared. Females earn 30 percentage points lower as seen with other regressions and literature. Divorcees earn 30 percentage points less than their married counterparts. People with less than high school degrees earn 39 percentage points less while the people

with a college degree earn 60 percentage points higher than people with a high school degree, which is expected according to literature and other regressions. We also see that in the year 2013 and 2015 we get a 20 and 22 percentage point increase respectively. Figure 3 shows the difference in income between those with T1D and those without T1D. It shows that people without T1D get more income over time but as stated earlier results were not statistically significant.

VI. CONCLUSION

Since T1D is a disease that is not-predictable, it is an effective example for showing the direct effects of poor health on employability. It is normally quite hard to isolate the economic impact of poor health alone due to the fact that most diseases have an environmental, genetic or nutritional etiology. This is not the case for those with T1D, demonstrating the severity of economic consequences that may result from such non-predictable chronic illnesses.

Results from this study suggest that having T1D does, in fact, negatively affect labor force participation in the US. Analysis of MEPS data shows that there is an overall decrease in employability as defined by a lower rate of employment and an increase in the number of used sick days. We did not, however, see a statistically significant correlation between having T1D and income level; we therefore cannot conclude that having T1D would affect a person's income level. Treatment for T1D can be both time consuming and costly. Additionally, poorly managed T1D can lead to further complications including neuropathy, retinopathy, cardiovascular disease, hypoglycemia

and hyperglycemia. These disease-related complications would in turn lead to a further increase in use of sick days and potentially exclusion from the labor market.

TABLES

Table 1 ***Summary Statistics***

	(1) Diabetics (SD)	(2) Non Diabetics (SD)
Employed	0.6658	0.7842
	(0.4558)	(0.3881)
Sick days	4.4646	2.8265
	(10.0781)	(8.7888)
Log of Sick Days	0.9119	0.5759
	(1.1130)	(0.9542)
Wage	23211.7213	30740.4682
	(30264.1850)	(32982.5301)
Log of Wage	7.1859	8.3875
	(4.5244)	(3.9629)
Age	36.3115	37.2295
	(7.4255)	(7.5536)
Nonwhite	0.2623	0.2968
	(0.4411)	(0.4568)
Female	0.5628	0.5334
	(0.4974)	(0.4989)
Cancer	0.0929	0.0325
	(0.2911)	(0.1773)
Arthritis	0.1585	0.1176
	(0.3662)	(0.3221)
Married	(0.4372)	(0.5362)
	(0.4974)	(0.4987)
Widowed	0.0000	0.0070
	(0.0000)	(0.0831)
Divorced	0.1530	0.1003
	(0.3610)	(0.3004)

Separated	0.0273	0.0354
	(0.1635)	(0.1847)
Never Married	0.3825	0.3211
	(0.4873)	(0.4669)
Less than HS	0.1597	0.1731
	(0.3676)	(0.3784)
High School Degree	0.6389	0.5602
	(0.4820)	(0.4964)
College Degree	0.2014	0.2667
	(0.4024)	(0.4422)

Standard deviation in parentheses

Table 2 ***Employment Regressions***

	(1) OLS	(2) PS Logit	(3) PS ATE	(4) PS ATT	(5) Entropy Balance
Type 1 Diabetes	-0.115**		-0.166***	-0.163***	-0.115***
	(0.0358)		(0.0461)	(0.0347)	(0.0325)
Age	0.00436	0.0489			0.00250
	(0.00295)	(0.126)			(0.0241)
Age squared	-0.0000428	0.000908			0.0000606
	(0.0000391)	(0.00169)			(0.000319)
Nonwhite	-0.0385***	-0.276			-0.0958**
	(0.00441)	(0.198)			(0.0369)
Midwest	0.0397***	0.105			-0.0852
	(0.00660)	(0.297)			(0.0515)
South	0.0148*	0.249			-0.163***
	(0.00598)	(0.260)			(0.0443)
West	0.0141*	-0.000562			-0.0678
	(0.00621)	(0.281)			(0.0455)
Cancer	-0.0400**	1.379***			0.0924*
	(0.0123)	(0.270)			(0.0462)
Arthritis	-0.137***	0.275			-0.224***
	(0.00709)	(0.241)			(0.0480)
Female	-0.151***	-0.0193			-0.174***
	(0.00387)	(0.172)			(0.0349)
Widowed	-0.0781**	0			-0.0458
	(0.0291)	(.)			(0.0450)
Divorced	0.0393***	0.559*			0.0571
	(0.00656)	(0.261)			(0.0527)
Separated	-0.000886	0.150			-0.0934
	(0.0113)	(0.472)			(0.0917)

Never Married	-0.0256***	0.492*			-0.0591
	(0.00471)	(0.200)			(0.0363)
Less than HS	-0.132***	-0.172			-0.138**
	(0.00608)	(0.237)			(0.0479)
College Degree	0.101***	-0.304			0.0355
	(0.00406)	(0.216)			(0.0411)
year=2012	-0.0109	0.0414			0.0472
	(0.00681)	(0.284)			(0.0567)
year=2013	-0.00111	-0.591			-0.0931
	(0.00680)	(0.336)			(0.0666)
year=2014	0.00732	0.147			0.0199
	(0.00688)	(0.284)			(0.0565)
year=2015	0.0191**	0.0226			0.0830
	(0.00602)	(0.258)			(0.0501)
Constant	0.774***	-6.330**			1.014*
	(0.0548)	(2.318)			(0.451)
Observations	36549	36312	36312	36312	36549

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ OLS (Ordinary Least Squared) PS ATE (Propensity score Average Treatment Effects) PS ATT (Propensity score Average Treatment Effects on the Treated)

Table 3 ***Sick Days Regressions***

	(1) OLS	(2) PS Logit	(3) PS ATE	(4) PS ATT	(5) Entropy Balance
Type 1 Diabetes	0.280*		0.182	0.465***	0.292**
	(0.110)		(0.0978)	(0.104)	(0.108)
Age	0.0183*	0.0489			0.0291
	(0.00819)	(0.126)			(0.0616)
Age squared	0.000308**	-0.000908			-0.000481
	(0.000109)	(0.00169)			(0.000829)
Nonwhite	-0.0355**	-0.276			0.117
	(0.0124)	(0.198)			(0.112)
Midwest	0.0413*	0.105			-0.0288
	(0.0192)	(0.297)			(0.162)
South	-0.0439**	0.249			-0.0467
	(0.0166)	(0.260)			(0.160)
West	-0.0000388	-0.000562			0.0772
	(0.0174)	(0.281)			(0.163)
Cancer	0.355***	1.379***			0.364*
	(0.0405)	(0.270)			(0.168)
Arthritis	0.436***	0.275			0.324*
	(0.0228)	(0.241)			(0.138)
Female	0.215***	-0.0193			0.159
	(0.0110)	(0.172)			(0.0909)
Widowed	0.0935	0			0.185
	(0.0826)	(.)			(0.131)
Divorced	0.114***	0.559*			0.219
	(0.0201)	(0.261)			(0.172)
Separated	0.0543	0.150			0.211
	(0.0313)	(0.472)			(0.228)
Never Married	0.0206	0.492*			0.0769

	(0.0131)	(0.200)			(0.109)
Less than HS	-0.131***	-0.172			0.0604
	(0.0154)	(0.237)			(0.170)
College Degree	0.0238	-0.304			0.134
	(0.0125)	(0.216)			(0.119)
year=2012	-0.0267	0.0414			-0.276
	(0.0179)	(0.284)			(0.157)
year=2013	0.0628***	-0.591			0.00741
	(0.0184)	(0.336)			(0.172)
year=2014	0.0340	0.147			0.0106
	(0.0185)	(0.284)			(0.171)
year=2015	0.193***	0.0226			0.341*
	(0.0170)	(0.258)			(0.166)
Constant	0.138	-6.330**			-0.0938
	(0.152)	(2.318)			(1.124)
Observations	30118	36312	29949	29949	30118

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ OLS (Ordinary Least Squared) PS ATE (Propensity score Average Treatment Effects) PS ATT (Propensity score Average Treatment Effects on the Treated)

Table 4 ***Wage Regressions***

	(1) OLS	(2) PS Logit	(3) PS ATE	(4) PS ATT	(5) Entropy Balance
Type 1 Diabetes	-1.080**		-1.489***	-1.517***	-1.079**
	(0.360)		(0.430)	(0.395)	(0.329)
Age	0.0650*	0.0489			-0.125
	(0.0296)	(0.126)			(0.245)
Age squared	-0.000698	-0.000908			0.00133
	(0.000392)	(0.00169)			(0.00326)
Nonwhite	-0.361***	-0.276			-0.437
	(0.0444)	(0.198)			(0.367)
Midwest	0.337***	0.105			-0.696
	(0.0669)	(0.297)			(0.508)
South	0.109	0.249			-1.407**
	(0.0605)	(0.260)			(0.445)
West	0.140*	-0.000562			-0.374
	(0.0631)	(0.281)			(0.451)
Cancer	-0.436***	1.379***			0.801
	(0.126)	(0.270)			(0.444)
Arthritis	-1.324***	0.275			-2.181***
	(0.0721)	(0.241)			(0.529)
Female	-1.673***	-0.0193			-2.020***
	(0.0390)	(0.172)			(0.358)
Widowed	-0.598*	0			-0.188
	(0.290)	(.)			(0.445)
Divorced	0.505***	0.559*			0.677
	(0.0648)	(0.261)			(0.511)
Separated	0.118	0.150			-0.859
	(0.111)	(0.472)			(0.920)
Never Married	-0.268***	0.492*			-0.480

	(0.0471)	(0.200)			(0.371)
Less than HS	-1.550***	-0.172			-1.292**
	(0.0602)	(0.237)			(0.499)
College Degree	1.422***	-0.304			0.478
	(0.0418)	(0.216)			(0.437)
year=2012	-0.0988	0.0414			0.00981
	(0.0684)	(0.284)			(0.529)
year=2013	0.0124	-0.591			-1.381
	(0.0684)	(0.336)			(0.728)
year=2014	0.0798	0.147			-0.127
	(0.0692)	(0.284)			(0.513)
year=2015	0.191**	0.0226			0.425
	(0.0605)	(0.258)			(0.453)
Constant	7.905***	-6.330**			13.52**
	(0.549)	(2.318)			(4.571)
Observations	36549	36312	36312	36312	36549

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ OLS (Ordinary Least Squared) PS ATE (Propensity score Average Treatment Effects) PS ATT (Propensity score Average Treatment Effects on the Treated)

FIGURES

Figure 1| Employment Rate Predictive Margins in Those With and Without T1D

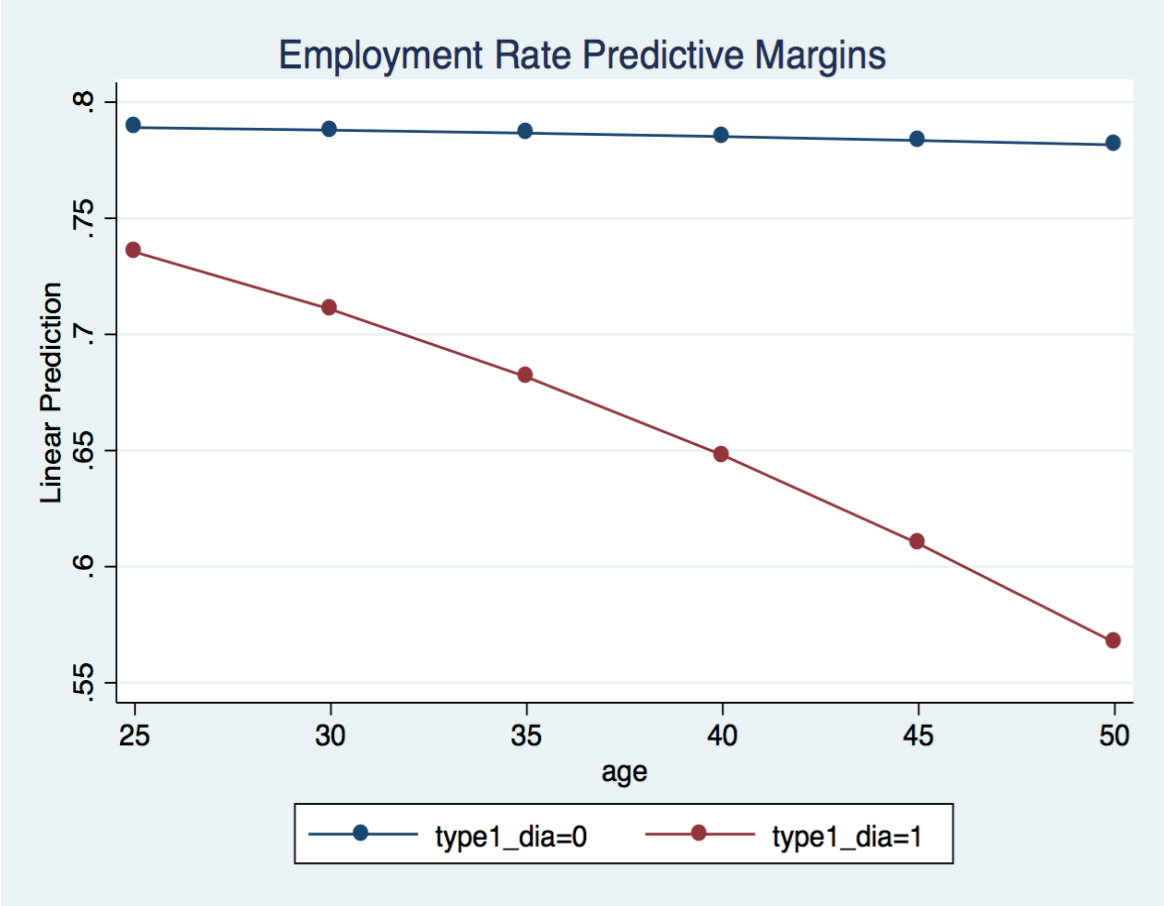


Figure 2| Sick Days Predictive Margins in Those With and Without T1D

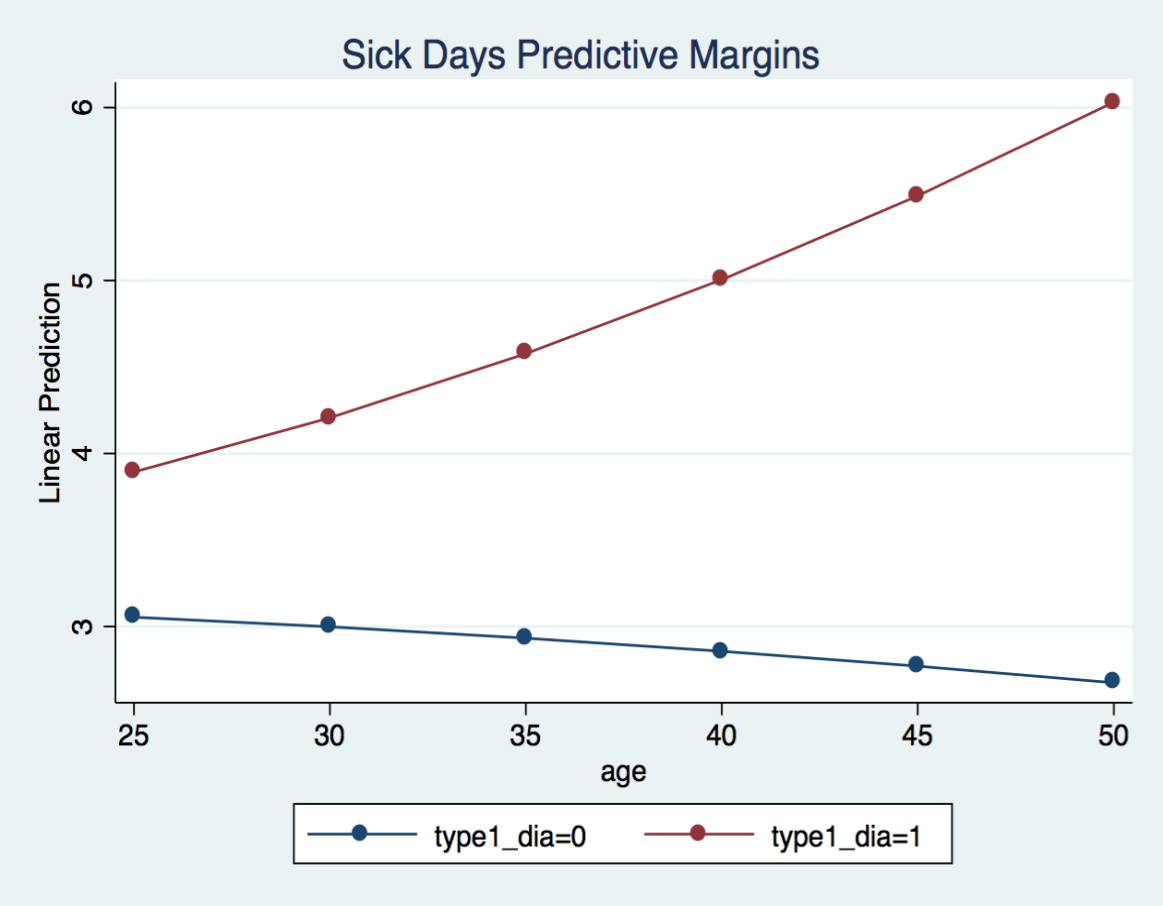
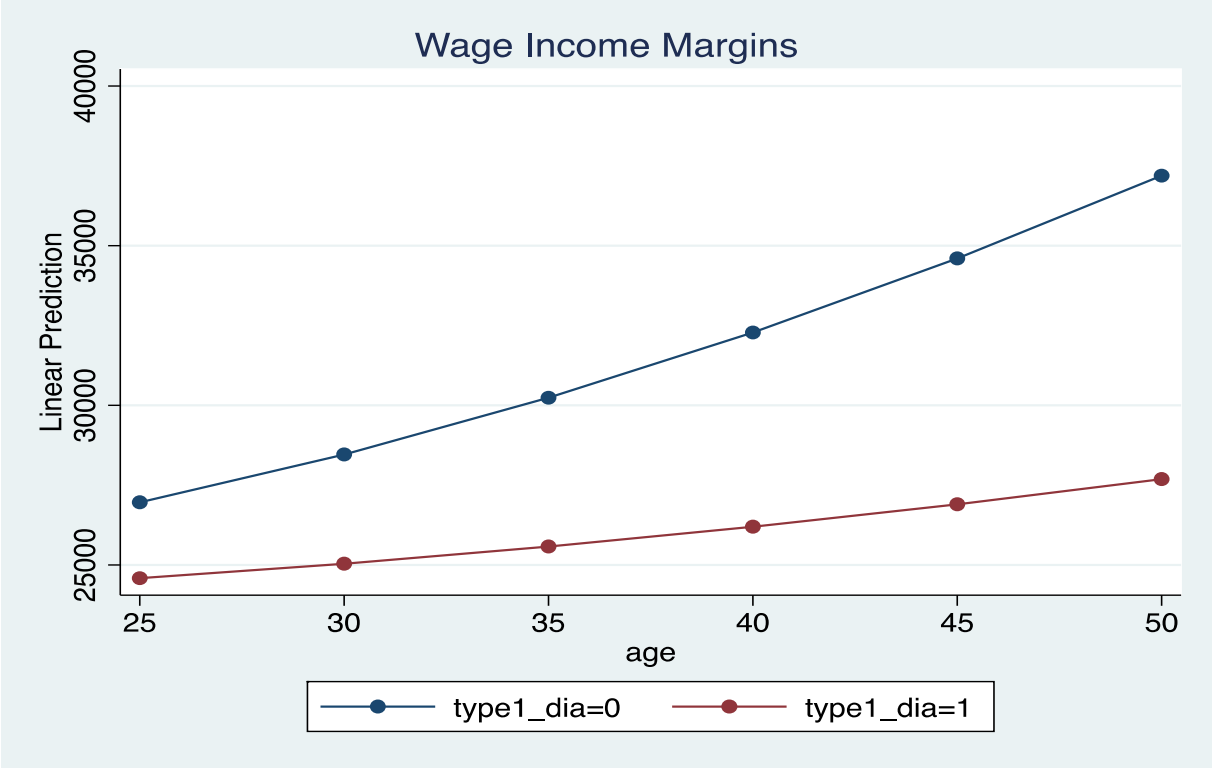


Figure 3| Wage Income Predictive Margins in Those With and Without T1D



References:

Brod, M., Christensen, T., Thomsen, T. L., & Bushnell, D. M. (2011). The Impact of Non-Severe Hypoglycemic Events on Work Productivity and Diabetes Management. *JVAL*, *14*, 665–671. https://doi.org/10.1016/j.jval.2011.02.001

Cnop, M., Welsh, N., Jonas, J. C., Jorns, a, Lenzen, S., & Eizirik, D. L. (2005). Mechanisms of pancreatic beta-cell death in type 1 and type 2 diabetes: many differences, few similarities. *Diabetes*, *54 Suppl 2*(6), S97-107. https://doi.org/10.2337/diabetes.54.suppl_2.S97

Dall, T. M., Mann, S. E., Zhang, Y., Quick, W. W., Seifert, R. F., Martin, J., … Zhang, S. (2009). Distinguishing the Economic Costs Associated with Type 1 and Type 2 Diabetes. *Population Health Management*, *12*(2), 103–110. https://doi.org/10.1089/pop.2009.12203

Dall, T. M., Zhang, Y., Chen, Y. J., Quick, W. W., Yang, W. G., & Fogli, J. (2010). The economic burden of diabetes. *Health Affairs (Project Hope)*, *29*(2), 297–303. https://doi.org/10.1377/hlthaff.2009.0155

Diseases, N. I. of D. and D. K. (2017). National Diabetes Statistics Report, 2017 Estimates of Diabetes and Its Burden in the United States Background. Retrieved from https://www.cdc.gov/diabetes/pdfs/data/statistics/national-diabetes-statistics-report.pdf

Federation, T. I. D. (n.d.). List of countries by incidence of Type 1 diabetes ages 0 to 14 | Diabetes UK. Retrieved July 2, 2018, from https://www.diabetes.org.uk/about_us/news_landing_page/uk-has-worlds-5th-highest-rate-of-type-1-diabetes-in-children/list-of-countries-by-incidence-of-type-1-diabetes-ages-0-to-14

Geelhoed-Duijvestijn, P. H., Pedersen-Bjergaard, U., Weitgasser, R., Lahtela, J., Jensen, M. M., & Östenson, C.-G. (2013). Effects of patient-reported non-severe hypoglycemia on healthcare resource use, work-time loss, and wellbeing in insulin-treated patients with diabetes in seven European countries. *Journal of Medical Economics*, *16*(12), 1453–1461. https://doi.org/10.3111/13696998.2013.852098

Hainmueller, J. (2012). Entropy Balancing for Causal Effects : A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies, 25–46. https://doi.org/10.1093/pan/mpr025

Katsarou, A., Gudbjörnsdottir, S., Rawshani, A., Dabelea, D., Bonifacio, E., Anderson, B. J., … Lernmark, Å. (2017). Type 1 diabetes mellitus. *Nature Reviews Disease Primers*, *3*, 17016. https://doi.org/10.1038/nrdp.2017.16

López-Bastida, J., López-Siguero, J. P., Oliva-Moreno, J., Perez-Nieves, M., Villoro, R., Dilla, T., … Vázquez, L. A. (2017). Social economic costs of type 1 diabetes mellitus in pediatric patients in Spain: CHRYSTAL observational study. *Diabetes Research and Clinical Practice*, *127*, 59–69. https://doi.org/10.1016/j.diabres.2017.02.033

Milton, B., Holland, P., & Whitehead, M. (2006). The social and economic consequences of childhood-onset Type 1 diabetes mellitus across the lifecourse: A systematic review. *Diabetic Medicine*, *23*(8), 821–829. https://doi.org/10.1111/j.1464-5491.2006.01796.x

Nielsen, H. B., Ovesen, L. L., Mortensen, L. H., Lau, C. J., & Joensen, L. E. (2016a).

Type 1 diabetes, quality of life, occupational status and education level â€“ A comparative population-based study. https://doi.org/10.1016/j.diabres.2016.08.021
Nielsen, H. B., Ovesen, L. L., Mortensen, L. H., Lau, C. J., & Joensen, L. E. (2016b). Type 1 diabetes, quality of life, occupational status and education level â€“ A comparative population-based study. *Diabetes Research and Clinical Practice*, *121*, 62–68. https://doi.org/10.1016/j.diabres.2016.08.021
Ortega, F. B., & Lavie, C. J. (2018). Progress in Cardiovascular Diseases Introduction and Update on Obesity and Cardiovascular Diseases 2018. *Progress in Cardiovascular Diseases*, *61*(2), 87–88. https://doi.org/10.1016/j.pcad.2018.07.009
Persson, S., Dahlquist, G., Gerdtham, U.-G., & Steen Carlsson, K. (2018). Why childhood-onset type 1 diabetes impacts labour market outcomes: a mediation analysis. *Diabetologia*, *61*(2), 342–353. https://doi.org/10.1007/s00125-017-4472-3
Roberts, B. T., & Smith, J. (2018). *Recent Advances & Emerging Opportunities*. *NIDDK*. Retrieved from https://www.niddk.nih.gov/about-niddk/strategic-plans-reports/niddk-recent-advances-emerging-opportunities-2018
Saberzadeh-Ardestani, B., Karamzadeh, R., Basiri, M., Hajizadeh-Saffar, E., Farhadi, A., Shapiro, A. M. J., … Baharvand, H. (2018). Type 1 Diabetes Mellitus: Cellular and Molecular Pathophysiology at A Glance. *Cell Journal*, *20*(3), 294–301. https://doi.org/10.22074/cellj.2018.5513
Songer, T. J., Laporte, R. E., Dorman, J. S., Orchard, T., Becker, D. J., & Drash, A. L. (1989). Employment Spectrum of IDDM. *Diabetes Care*, *12*(9), 615–622.
Steen Carlsson, K., Landin-Olsson, M., Nyström, L., Arnqvist, H. J., Bolinder, J., Östman, J., & Gudbjörnsdóttir, S. (2010). Long-term detrimental consequences of the onset of type 1 diabetes on annual earnings-evidence from annual registry data in 1990-2005. *Diabetologia*, *53*(6), 1084–1092. https://doi.org/10.1007/s00125-009-1625-z
Tao, B., Pietropaolo, M., Atkinson, M., Schatz, D., Taylor, D., & Van Baal, P. H. M. (2010). Estimating the Cost of Type 1 Diabetes in the U.S.: A Propensity Score Matching Method. https://doi.org/10.1371/journal.pone.0011501
Travis Minor. (2011). The effect of diabetes on female labor force decisions: new evidence from the National Health Interview Survey. *Health Economics*, *1486*(November 2010), 1468–1486. https://doi.org/10.1002/hec
Williams, R., & Farrar, H. (1986). *Diabetes Mellitus*. Littleton, Mass.: PSG Pub. Co.