



# The impact of diabetes on employment: genetic IVs in a bivariate probit

H. Shelton Brown III<sup>a</sup>, José A. Pagan<sup>b,c,\*</sup> and Elena Bastida<sup>d</sup>

<sup>a</sup>University of Texas School of Public Health, School of Public Health Building (RAHC), Texas, USA

<sup>b</sup>Robert Wood Johnson Health and Society Scholars Program, University of Pennsylvania, Pennsylvania, USA

<sup>c</sup>Department of Economics and Finance, University of Texas-Pan American, Texas, USA

<sup>d</sup>Department of Sociology and Center on Aging and Health, University of Texas-Pan American, Texas, USA

## Summary

Diabetes has been shown to have a detrimental impact on employment and labor market productivity, which results in lost work days and higher mortality/disability. This study utilizes data from the Border Epidemiologic Study on Aging to analyze the endogeneity of diabetes in an employment model. We use family history of diabetes as genetic instrumental variables. We show that assuming that diabetes is an exogenous variable results in an overestimate (underestimate) of the negative impact of diabetes on female (male) employment. Our results are particularly relevant in the case of populations where genetic predisposition has an important role in the etiology of diabetes. Copyright © 2004 John Wiley & Sons, Ltd.

**Keywords** diabetes; IV; econometrics

## Introduction

A recent report from the American Diabetes Association (ADA) estimates that the economic cost of diabetes in the US amounted to \$132 billion in 2002. About \$39.8 billion of these losses can be attributed to lost productivity in terms of lost work days, restricted activity days, permanent disability and mortality [1]. The medical costs of treating the 12.1 million people with diabetes is twice as high as those incurred in treating non-diabetics [1,2].

Increasing obesity, high immigration rates for groups at high risk for diabetes such as Hispanics, and population aging are likely to lead to a substantial increase in the US population with diabetes in the near future. The US Census Bureau estimates that from 2002 to 2020 the number of

individuals diagnosed with diabetes will increase by 44% to 17.4 million, with an economic cost of \$192 billion to the US economy in 2002 dollars [1]. With the prevalence and incidence of diabetes increasing, accurate estimates of the labor market cost of diabetes are important in order to develop appropriate health policy responses.

Studies analyzing the impact of diabetes on employment assume that diabetes is an exogenous variable [3–6]. However, diabetes could be correlated with unmeasured factors that are related to employment status. For example, unmeasured personal traits that are positively related to employment, such as motivation or drive, could also influence lifestyle choices and ultimately decrease the onset of diabetes. Being out of work could also lead to behavioral changes that affect health status and the development of diabetes.

\*Correspondence to: 3641 Locust Walk, Philadelphia, Pennsylvania 19104, USA.

E-mail: pagan@wharton.upenn.edu

The rise in the prevalence of diabetes has been mainly due to changes in behavior over time rather than to changes in the genetic base. Some population groups, especially Hispanics, are more likely to be genetically predisposed to diabetes, [7–9]. However, many who are predisposed do not become diabetic. The difference in many cases is behavioral, which is only partially observed. It may be that those that are genetically predisposed to developing diabetes, but who avoid it through behavior, also enjoy labor market success.

While the diabetes prevalence is rising, it is not clear that the labor costs per diabetic are increasing. According to the ADA, the proportion of labor costs among total costs attributed to diabetes fell by 45% between 1997 and 2002, from \$60.5 to \$39.8 billion in 2002 dollars [10,1].<sup>a</sup> Therefore, it may be that as the prevalence of diabetes has risen, the average labor market costs of diabetes have fallen. For instance, technological changes over the last three decades have led to increases in the number of jobs that are less physically demanding [4].

This study addresses the endogeneity of diabetes by using family history of diabetes variables as ‘genetic’ instrumental variables (IVs). Family history of diabetes is related to whether a person is genetically predisposed to developing diabetes and, at least in our sample, it is unlikely to be related to employment and labor market success.<sup>b</sup> Although there is some evidence that genetics also influences the age at onset [11, 12] and the severity of diabetes [13], we show that this is unlikely to bias our estimates in our population under study.

The genetic risk factor of diabetes is particularly relevant for Hispanics because they have Native American and African genes, which are populations who exhibit a high prevalence of diabetes [7].<sup>c</sup> Genetically, Mexican Americans are 31% Native American and 9% African [14, 8].

We use microdata from the Border Epidemiologic Study on Aging (BESA), an ongoing survey from a predominantly Mexican American area of South Texas, to analyze how diabetes is related to employment. The BESA data has two important advantages. First, BESA surveys Hispanics, who have a high prevalence and incidence of diabetes. The Hispanic population diagnosed with this health condition is expected to rise from 1.4 million in 2002 to 2.9 million in 2020, a 107% increase [1]. In contrast, the total US population diagnosed with diabetes is expected to increase by 44% during the same time period. Second, unlike

national surveys like the *Health and Retirement Study* or the *National Health Interview Survey*, BESA includes several questions on the respondent’s family history of diabetes.

## Data and methods

The Border Epidemiologic Study on Aging is a population based study of community dwelling Mexican Americans aged 45 and older residing in the US/Mexico border area of South Texas. This region is known as the Lower Rio Grande Valley (LRGV) and it is one of the poorest areas in the US [15]. Moreover, the health and economic disparities between the LRGV, Texas and the US are often large (see Table 1) [16].

BESA includes extensive socioeconomic, demographic and health information on a sample of 1089 respondents. Detailed information on the sampling design has been discussed elsewhere [3]. After excluding observations with missing values in the variables of interest, the sample size falls to 989 respondents.

For the purpose of this study, the key advantage of BESA is that the respondent’s family history of diabetes is available. More specifically, respondents were asked whether their parents, grandparents, brothers and sisters have diabetes. Although it is possible that IVs based on the family history of diabetes capture the same household shared environment instead of genetic

Table 1. Selected socio-demographic and health characteristics (%)

	LRGV	Texas	US
65 years and over <sup>a</sup>	10.2	9.9	12.4
African American <sup>a</sup>	0.5	11.5	12.3
Hispanic <sup>a</sup>	87.4	32.0	12.5
Below poverty level <sup>a</sup>	35.2	15.0	12.4
% US income <sup>b</sup>	51.0	92.6	100
Diabetes <sup>b</sup>	7.8	6.2	6.7
Hypertension <sup>b</sup>	24.2	25.8	28.7
Hispanic breast cancer <sup>c</sup>	78.9	81.9	89.8
Hispanic prostate cancer <sup>c</sup>	114.6	107.2	137.2

<sup>a</sup>2000 Census American Factfinder.

<sup>b</sup>2001 Behavioral Risk Factor Surveillance System.

<sup>c</sup>Age-adjusted per 100000, 1996–2000 Texas Cancer Registry, Texas Department of Health and National Cancer Registry.

risk factors, this is unlikely in a sample of adults aged 45 and older because siblings are less likely to live together as they get older.

As mentioned above, studies on the relationship between diabetes and employment assume that diabetes is an exogenous variable [3–6]. However, this health condition is likely to be correlated with observable but unmeasured individual characteristics as well as unobservable factors (such as ability or motivation) that could also affect employment status. For example, unmeasured personal traits that increase the employment propensity could also increase the probability of having a healthier lifestyle and decrease the chances of developing diabetes. Also, being unemployed or out of the labor force could lead to unhealthy behavior that ultimately results in the development of diabetes.

To account for the possibility of endogeneity and unobserved heterogeneity, we model diabetes as a binary regressor in a recursive simultaneous-equations probit model of the determinants of employment. Estimating this model is straightforward because the likelihood function of a recursive probit is identical to that of a bivariate probit model of employment and diabetes in which the endogenous diabetes binary variable is included in the employment equation as simply another regressor [17, 18].

Let  $Diab_i$  be a binary endogenous dummy ( $Diab_i = 1$  if diabetetic, 0 otherwise). The employment equation is given by

$$Empl_i^* = x_i'\beta + Diab_i\gamma + e_i \quad (1)$$

where  $Empl_i^* > 0$  ( $Empl_i = 1$ ) and  $Empl_i^* < 0$  ( $Empl_i = 0$ ) indicate that individual  $i$  is employed or otherwise, respectively,  $x_i$  is a vector of factors that affect the employment decision,  $\beta$  is the associated vector of coefficients,  $\gamma$  is the diabetes dummy coefficient and  $e_i$  is a stochastic error term.

The diabetes equation is given by

$$Diab_i^* = x_i'\alpha + f_i'\delta + u_i \quad (2)$$

where  $Diab_i^* > 0$  ( $Diab_i = 1$ ) and  $Diab_i^* < 0$  ( $Diab_i = 0$ ) indicate that individual  $i$  is diabetetic or not, respectively,  $f_i$  is a vector of instrumental variables representing the family history of diabetes,  $\delta$  is the associated vector of coefficients and  $u_i$  is a stochastic error term.

If  $e$  and  $u$  in Equations (1) and (2) are not independent due to the endogeneity of  $Diab_i$ , the estimated parameters of Equation (1) will not be consistent if the two equations are estimated by

univariate probits. However, estimating the employment and diabetes equations jointly in a bivariate probit will yield consistent estimates when  $e$  and  $u$  are not independent [19, 20].

Greene argues that the bivariate probit approach is more efficient than the commonly employed two-step procedure because the latter does not take into account the correlation between the disturbances of the employment and diabetes equations [17].<sup>d</sup> Equations (1) and (2) are estimated by full-information maximum likelihood. Knapp and Seaks show that a likelihood-ratio test of whether the correlation coefficient of the residuals in Equations (1) and (2) is equal to zero can be used as a Hausman endogeneity test [20].

## Results

Table 2 reports the descriptive statistics of the variables used in the employment and diabetes equations by gender. Employment status refers to whether the person was employed at the time of the interview. Note that women have lower employment rates and schooling than men, are more likely to be immigrants and have less English proficiency. 23.7% of women have been diagnosed with diabetes compared with 16.6% of men. Interestingly, 31.6% (20.4%) of women (men) have diabetetic siblings and 22.6% (15.7%) have a diabetetic mother. About 11.2% (7.7%) of women (men) have a diabetetic father and 3.5% (3.6%) have a diabetetic grandparent. Thus, the family history of diabetes is more pronounced among Mexican American women than men in this sample.

Table 3 reports the results of the employment probit regressions assuming that diabetes is exogenous. The coefficients of the control variables have the expected signs. These are the same control variables included in the Bastida and Pagán study [3]. The main results show that the diabetes coefficient is negative and highly statistically significant for both women and men, suggesting that diabetes has a detrimental effect on employment.

We estimated the marginal effect of diabetes as the change in the employment probability when the diabetes dummy changes from zero to one, and all the other variables are fixed at their means. The marginal effect for women is  $-0.075$  and for men it is  $-0.074$ ; that is, the employment propensity of diabetetics is 7.4–7.5 percentage points lower than

Table 2. Descriptive statistics, by gender

Variable	Women		Men	
	Mean	SD	Mean	SD
Employed (1 = yes; 0 = no)	0.264	0.441	0.367	0.483
Years of schooling	5.955	4.506	8.408	6.144
Age	62.005	10.794	62.243	10.903
Age squared/100	39.609	13.782	39.927	13.886
Married (1 = yes; 0 = no)	0.501	0.500	0.763	0.426
Immigrant (1 = yes; 0 = no)	0.485	0.500	0.411	0.493
Years residing in the US	14.551	20.076	11.559	18.897
Speaks English well (1 = yes; 0 = no)	0.590	0.492	0.737	0.441
Number of own children	3.948	2.591	3.654	2.500
Household head (1 = yes; 0 = no)	0.680	0.467	0.870	0.337
Owens home (1 = yes; 0 = no)	0.768	0.422	0.796	0.404
Log of other household income	3.005	4.369	4.164	4.686
Diagnosed with diabetes (1 = yes; 0 = no)	0.237	0.425	0.166	0.372
Diabetic sibling (1 = yes; 0 = no)	0.316	0.465	0.204	0.404
Diabetic mother (1 = yes; 0 = no)	0.226	0.418	0.157	0.364
Diabetic father (1 = yes; 0 = no)	0.112	0.316	0.077	0.267
Diabetic grandparent (1 = yes; 0 = no)	0.035	0.185	0.036	0.185
<i>N</i>	651		338	

Table 3. Employment probit, by gender

Variable	Women		Men	
	Coefficient	(Std err.)	Coefficient	(Std err.)
Constant	-1.426	(2.927)	-12.077	(8.084)
Years of schooling	0.097***	(0.018)	0.119***	(0.026)
Age	0.071	(0.099)	0.500*	(0.284)
Age squared/100	-0.114	(0.083)	-0.563**	(0.250)
Married (1 = yes; 0 = no)	-0.687***	(0.191)	-0.025	(0.300)
Immigrant (1 = yes; 0 = no)	0.207	(0.243)	-0.327	(0.424)
Years residing in the US	0.002	(0.006)	0.030**	(0.012)
Speaks English well (1 = yes; 0 = no)	0.328*	(0.175)	0.571	(0.359)
Number of own children	-0.060**	(0.028)	-0.051	(0.056)
Household head (1 = yes; 0 = no)	0.004	(0.163)	-0.109	(0.383)
Owens home (1 = yes; 0 = no)	0.073	(0.167)	1.110***	(0.321)
Log of other household income	0.082***	(0.019)	-0.034	(0.025)
Diagnosed with diabetes (1 = yes; 0 = no)	-0.341**	(0.173)	-1.015***	(0.355)
<i>N</i>	651		338	
Log-likelihood	-243.529		-81.839	
$\chi^2_{(12)}$	264.735***		280.633***	

Significance levels: \*10%, \*\*5%, \*\*\*1%.

that of non-diabetics. These results are qualitatively consistent with those found in previous research and they are reported here for comparative purposes [3–6].

Table 4 reports the results of the diabetes probit equations that include all the exogenous regressors of the employment probit plus the family history of diabetes, our genetic predisposition IVs. Recent

research has shown that there could be a large inconsistency in IV estimates if the instruments are weakly correlated with the endogenous variable [21, 22]. As such, we report the change in the Pseudo- $R^2$  and a likelihood ratio test of the genetic IVs.

The pseudo- $R^2$  changes by about 0.10 for both women and men. Moreover, the sibling, mother, father and grandparent diabetes dummies are all positive, and five out of the eight regression coefficients are statistically significant at conventional levels. A likelihood ratio test of the joint statistical significance of the genetic predisposition IVs suggest that these are reasonably good indicators of diabetes for both women and men (see Table 4, bottom). The  $\chi^2_{(4)}$  values are 71.9 and 26.3, and they are both statistically significant at the 1% level.

Another source of concern is whether our IVs are associated with unobserved factors related to employment and labor market success. This is important because studies have shown that genetics could also influence the age at onset [11, 12] and

the severity of diabetes [13], which in turn may be related to employment. If this is the case then the assumption that IVs are uncorrelated with the error term of the employment equation would be suspect. Our IVs should be independent of factors such as, for example, age at onset and comorbidities.

Although we do not have information on the age at onset of diabetes, we do have information on conditions related to diabetes (heart disease, high-blood pressure, stroke and visual impairment) and comorbid conditions unrelated to diabetes (cancer, bone/joint problems and hearing impairment) [23]. We test for the independence of our IVs by estimating probit models of the association between the genetic IVs and these health conditions. We do not find any strong statistical evidence that these health conditions are related to our genetic IVs. In the case of women, only having high-blood pressure is positively associated with having a sibling with diabetes. In the case of men, cancer is the only condition to be positively related with having a sibling or father

Table 4. Diabetes probit, by gender

Variable	Women		Men	
	Coefficient	(Std err.)	Coefficient	(Std err.)
Constant	-7.852***	(2.249)	-7.454**	(3.411)
Years of schooling	-0.011	(0.017)	-0.028	(0.021)
Age	0.212***	(0.070)	0.171	(0.106)
Age squared/100	-0.154***	(0.055)	-0.117	(0.081)
Married (1 = yes; 0 = no)	0.017	(0.168)	-0.016	(0.224)
Immigrant (1 = yes; 0 = no)	-0.558***	(0.212)	0.744**	(0.290)
Years residing in the US	0.005	(0.005)	-0.010	(0.007)
Speaks English well (1 = yes; 0 = no)	-0.371**	(0.157)	0.368	(0.250)
Number of own children	-0.060**	(0.028)	-0.034	(0.036)
Household head (1 = yes; 0 = no)	-0.129	(0.146)	0.085	(0.282)
Owens home (1 = yes; 0 = no)	0.200	(0.148)	0.070	(0.233)
Log of other household income	-0.035*	(0.019)	-0.031	(0.021)
Diabetic sibling (1 = yes; 0 = no)	0.652***	(0.124)	0.604***	(0.203)
Diabetic mother (1 = yes; 0 = no)	0.603***	(0.138)	0.652***	(0.241)
Diabetic father (1 = yes; 0 = no)	0.155	(0.184)	0.483	(0.313)
Diabetic grandparent (1 = yes; 0 = no)	0.653**	(0.296)	0.561	(0.510)
<i>N</i>	651		338	
Log-likelihood	-299.325		-128.913	
$\chi^2_{(15)}$	113.649***		45.678***	
Pseudo- $R^2$	0.151		0.160	
Change in pseudo- $R^2$ of genetic IVs	0.101		0.096	
$\chi^2_{(4)}$ (LR test of genetic IVs)	71.890***		26.321***	

Significance levels: \*10%, \*\*5%, \*\*\*1%.

Table 5. Bivariate probit employment, by gender

Variable	Women		Men	
	Coefficient	(Std err.)	Coefficient	(Std err.)
Constant	0.121	(2.887)	-12.753	(7.839)
Years of schooling	0.096***	(0.018)	0.112***	(0.027)
Age	0.014	(0.098)	0.522*	(0.275)
Age squared/100	-0.114	(0.083)	-0.575**	(0.242)
Married (1 = yes; 0 = no)	-0.642***	(0.187)	-0.071	(0.296)
Immigrant (1 = yes; 0 = no)	0.314	(0.238)	-0.238	(0.424)
Years residing in the US	0.001	(0.006)	0.028**	(0.012)
Speaks English well (1 = yes; 0 = no)	0.336**	(0.169)	0.613*	(0.351)
Number of own children	-0.064**	(0.027)	-0.052	(0.054)
Household head (1 = yes; 0 = no)	0.022	(0.157)	-0.106	(0.368)
Owens home (1 = yes; 0 = no)	0.007	(0.163)	1.084***	(0.322)
Log of other household income	0.084***	(0.019)	-0.036	(0.025)
Diagnosed with diabetes (1 = yes; 0 = no)	0.505	(0.384)	-1.705**	(0.806)
$\rho(e, u)$	-0.527**	(0.202)	0.428	(0.477)
<i>N</i>	651		338	
Log-likelihood	-4540.66		-210.468	
$\chi^2_{(27)}$	259.209***		126.701***	
Likelihood-ratio test of $\rho(e, u) = 0$				
$\chi^2_{(1)}$	4.388**		0.568	

Significance levels: \*10%, \*\*5%, \*\*\*1%.

with diabetes, but the relationship is marginally significant.

Table 5 reports the results of the bivariate probit model for both men and women. A likelihood-ratio (Hausman) test of the correlation coefficient of the disturbances suggests that diabetes is endogenous for women and exogenous for men (see Table 5, bottom). The negative sign of the  $\rho(e, u)$  coefficient for women suggests that unobserved and/or unmeasured factors that increase the probability of being diabetic also decrease their employment propensity. For men, the  $\rho(e, u)$  coefficient is positive but statistically insignificant, but the power is lower for men than for women.

Note that for women the estimated coefficient of the diabetes dummy is positive but it is statistically insignificant. For men, however, the coefficient is negative and statistically significant at the five percent level.<sup>e</sup> Based on the estimated parameters of the bivariate probit model, the marginal effect for the men diabetes dummy is -0.106; that is, the employment propensity of diabetic men is 10.6 percentage points lower than that of non-diabetic men.<sup>f</sup>

## Discussion and conclusion

The empirical analysis of this study suggests that not taking into account the endogeneity of diabetes could result in an overestimate of the negative impact of diabetes on female employment. In larger sample sizes, ignoring endogeneity could lead to an underestimate of the negative impact of diabetes on male employment. The bias seems to be larger for women than for men.

The results show that diabetes has a substantial negative effect on employment for men but not for women. The results are consistent with previous research suggesting that diabetes has a more severe labor market impact on men than on women [3].

Our findings are also consistent with studies showing that Hispanics with diabetes exhibit more complications related to this disease than non-Hispanic whites. Hispanic diabetics have higher rates of end-stage renal disease and retinopathy, and they have more functional status limitations than non-Hispanic whites [14].

From a health policy perspective, the results from this study suggest that cost estimates of the labor productivity losses associated with diabetes should consider the possibility of endogeneity biases related to diabetes. This is particularly relevant in the case of populations where genetic predispositions, as manifested by a family history of diabetes, play an important role in the etiology of diabetes. Past studies on diabetes and its costs have not addressed this methodological challenge. Although the results from this study are difficult to generalize to the overall population, the main findings have a wider methodological applicability in their contribution to the economic analysis of diabetes and its consequences.

### Acknowledgements

The authors gratefully acknowledge the financial support of the National Institutes of Health (NIH-NIGMS, Grant NIH #78BT498W) and the Robert Wood Johnson Health and Society Scholars Program. We thank Craig Hanis, Gautam Hazarika, Beth J. Soldo, Robert A. Aronowitz, David Asch, Dominick L. Frosch and Sonya Grier for helpful comments and suggestions.

### Notes

- a. This is a point not emphasized by the ADA study. Their methodology counts missed work days and permanent loss of work days for diabetics and non-diabetics.
- b. Related research has shown that the prevalence of diabetes in Mexican Americans is twice as high for those with diabetic parents than for those with no family history of the disease [8,9].
- c. The genetic component of diabetes is based on the evolution of a 'thrifty' genotype that controls the efficient storage of calories in feast and famine cycles. These cycles are now non-existent and food is plentiful, which has led to increases in the prevalence of diabetes in some populations, notably Native Americans [14].
- d. A two-step procedure would involve estimating the predicted probability of diabetes from a probit or linear probability model and then including this predicted variable in an employment probit model.
- e. We also estimated the models including the Body Mass Index (BMI) but the results did not change substantially. We report the results without BMI so that they are comparable with previous research [3].

- f. In the bivariate probit, the marginal effects of the exogenous variables in the employment equation are more difficult to estimate because they have a direct effect on employment and an indirect effect via the diabetes equation [18].

### References

1. American Diabetes Association. Economic costs of diabetes in the U.S. in 2002. *Diabetes Care* 2003; **26**(3): 917–932.
2. Pagano E, Brunetti M, Tediosi F, Garattini L. Cost of diabetes: a methodological analysis of the literature. *Pharmacoeconomics* 1999; **15**(6): 583–595.
3. Bastida E, Pagán JA. The impact of diabetes on adult employment and earnings of Mexican Americans: findings from a community based study. *Health Econ* 2002; **11**(5): 403–413.
4. Kahn M. Health and labor market performance: the case of diabetes. *J Labor Econ* 1998; **16**(4): 878–899.
5. Ng YC, Jacobs P, Johnson JA. Productivity losses associated with diabetes in the U.S. *Diabetes Care* 2001; **24**(2): 257–261.
6. Lavigne JE, Phelps CE, Mushlin A, Lednar WM. Reductions in individual work productivity associated with Type 2 diabetes mellitus. *Pharmacoeconomics* 2003; **21**(15): 1123–1134.
7. Hanis CL, Hewett-Emmett D, Bertin TK, Schull WJ. Origins of U.S. Hispanics: implications for diabetes. *Diabetes Care* 1991; **14**(7): 618–627.
8. National Diabetes Information Clearinghouse. *Diabetes in Hispanic Americans*, vol. 02-3265. National Institutes of Health: Bethesda, MD, 2002.
9. Stern MP, Gaskill SP, Hazuda HP, Gardner LI, Haffner SM. Does obesity explain excess prevalence of diabetes among Mexican Americans? Results of the San Antonio heart study. *Diabetologia* 1983; **24**: 272–272.
10. American Diabetes Association. Economic consequences of diabetes mellitus in the U.S. in 1997. American Diabetes Association. *Diabetes Care* 2001; **24**(2): 296–309.
11. Duggirala R, Almasy L, Blangero J, Jenkinson CP, Arya R, DeFronzo RA, Stern MP, O'Connell P. Further evidence for a type 2 diabetes susceptibility locus on chromosome 11q. *Genet Epidemiol* 2003; **24**(3): 240–242.
12. Wiltshire S, Frayling TM, Groves CJ, Levy JC, Hitman GA, Sampson M, Walker M, Menzel S, Hattersley AT, Cardon LR, McCarthy MI. Evidence from a large UK family collection that genes influencing age of onset of type 2 diabetes map to chromosome 12p and to the MODY3/NIDDM2 locus on 12q24. *Diabetes* 2004; **53**(3): 855–860.
13. The Diabetes Control and Complications Trial Research Group. Clustering of long-term complica-

- tions in families with diabetes in the diabetes control and complications trial. *Diabetes* 1997; **46**(11): 1829–1839.
14. Carter JS, Pugh JA, Monterrosa A. Non-insulin-dependent diabetes mellitus in minorities in the United States. *Ann Intern Med* 1996; **125**(3): 221–232.
  15. Brown CJ, Mora MT. Labor and demographic challenges of the US/Mexico border region. In *Worker Displacement in the US/Mexico Border Region: Issues and Challenges*, Chapter 2, Pagán JA (ed.), Edward Elgar: Colchester, UK, 2004; 6–22.
  16. Bastida E. Health and job displacement: the case of garment manufacturing workers on the US/Mexico border. In *Worker Displacement in the US/Mexico Border Region: Issues and Challenges*, Chapter 6, Pagán JA (ed.), Edward Elgar: Colchester, UK, 2004; 65–80.
  17. Greene WH. Gender economics courses in liberal arts colleges: further results. *J Econ Educ* 1998; **29**(4): 291–300.
  18. Greene WH. *Econometric Analysis* (5th edn). Prentice Hall: Upper Saddle River, NJ, 2003.
  19. Maddala GS. *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press: Cambridge, 1983.
  20. Knapp LG, Seaks TG. A Hausman test for a dummy variable in probit. *Appl Econ Lett* 1998; **5**: 321–323.
  21. Bound J, Jaeger DA, Baker RM. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *J Am Statist Assoc* 1995; **90**(430): 443–448.
  22. Staiger D, Stock JH. Instrumental variables regression with weak instruments. *Econometrica* 1997; **65**(3): 557–586.
  23. Maty SC, Fried LP, Volpato S, Williamson J, Brancati FL, Blaum CS. Patterns of disability related to diabetes mellitus in older women. *J Gerontol Med Sci* 2004; **59A**(2): 148–153.