Incidence of depression on labor supply decissions.

David Cantarero Prieto[1],
Patricia Moreno Mencía[2] and
Juan Rodriguez Poo[3]

[1−2−3] Department of Economics.
University of Cantabria, Av. Los Castros, s/n. Santander.

[1]david.cantarero@unican.es, [2]patricia.moreno@unican.com, [3]juan.rodriguez@unican.es

October 29, 2014

Abstract

This paper studies the estimation of the impact of a mental illness, such as the depression, on labor market decisions. We present a class of binary choice models for panel data with two main objectives to examine, the endogeneity of the depression and also the impact of controlling for unobserved heterogeneity. Sample selection and endogeneity are usual cases of biases in non-experimental studies so it is necessary to deal with them. Thus, using data from the Survey of Health, Ageing, Retirement and Employment of Europe (SHARE), we propose a model to deal with selectivity bias and to estimate other time invariant unobserved heterogeneity. Firstly, we propose a bivariate estimation to capture the correlation between the probability of being employed and having depression. In a second part, a generalization of this model is proposed with a switching binary panel-data model. Finally, we discuss the weakness of this approaches and propose a new model to relax strong assumptions.

1 Introduction

In this study our main concern is how to estimate the effect of endogenous binary variables in a binary response model. The problem mentioed is relevant in social science studies, which consists in general non experimental data. The depression is an often mental illness that has been shown to be strongly related with some important life outcomes, such as educational or labor market outcomes (Fletcher 2010, Berndt et al. 2000, Ettner et al. 1997, Marcotte and Wilcox-Gok 2003). According to the World Organization of the Health (WHO), 121 million people suffer from it today and about one in five adults would have had depressive symptoms sometime in their life. Following WHO predictions, it is hoped that disorders depressive, responsible for the fourth cause of death and disability worldwide, occupy second place, after heart disease, in 2020. Depression has had a very significant evolution of growth in recent years, resembling the intuitive idea of epidemy, this evolution needs a vigorous and urgent action. In addition to the treatments provided in hospitals, a social change and performance measures are required. Anxiety and depressive disorders are the most common mental disorders throughout life. According to the national survey of health (ENS) in 2006, the overall prevalence of depression, anxiety and other mental disorders among Spanish adults (from 16 years onwards) was 14.7%. The family doctor is in our country, who attends to more than 90% of patients with psychiatric disorders, detecting between 60-80% of depression and 30-60% of anxiety disorders. And, between 25-33% of patients consulting a family physician presents a psychiatric disorder.

The literature reviewed about the depression suggests that some of the depressive symptoms are different in function of the individual characteristics such as the age, the gender or the kind of illnesses suffered. McNeil and Harsany (1989) showed that old people tend to manifest less the emotional symptoms to the doctor than the youngest. Maes (2002) obtained that older people had greater relevance of certain depressive symptoms such as weight problems, lack of reactivity , depressed mood , loss of interest , insomnia, allergies , anxiety, loss of self-esteem, psychotic symptoms and psychomotor retardation. Several authors believe that depression is more related to the existence of other diseases; Franco, Sanmartin, Ouija and Giles (2003) concluded that the symptoms that differentiate depression between elder and young adult are those relating to the deadening or future loss.

According to a study published in the British Journal of Psychiatry (King et al., 2008) , the Spanish women are the Europeans who most often suffer from depression and anxiety. The study was conducted with a sample of 7,000 primary care patients in six European countries: Spain , UK, Portugal , Slovenia , Estonia and the Netherlands. Duque Gonzalez et al. (2009) estimated that mental illnesses are the second leading cause of permanent and temporary sick leave at work, besides being the fourth leading cause of informal care (provided by persons who are not professional as such but mostly family) with data from 2002, the total cost of mental illness in Spain is estimated in about 7.019 million euros, being the direct medical costs the 39.6% about the 7.3% of the total public health expenditure in that year.

Other studies have examined the impact of mental disorders in the labor supply. Although there are several studies linking depression with labor market outcomes, the research of the intensity of the participation is less explored. The labor supply is associated with health outcomes (Deaton and Paxson, 1998; Currie,2009) and in that sense we think there is a negative relation; worse health implies less working hours. Chatterji et al. (2008) carried out an analysis relating this mental disorder with a reduction in labor participation (about 9-11 points) and pointed out that having a mental illness such as depression can suppose for the person a costly problem. Thus, there are mainly three aspects that relate depression with employment according to Chatterji et al.; Firstly the lack of motivation, secondly the discrimination because of the employer predjudice and finally the employer is unwillingness to incur in extra cost due to this illness.

In this study, we estimate the effects that depression has in labor supply decisions, being the labor market one of the most affected scenarios for that illness. Depressed people feel unmotivated with jobs, with large periods of inactivity or even abandoning the job definitively. This illness is one of the most common causes of health attention in primary care and it is also associated with the rate of chronic disability in individuals. A large body of empirical research have investigated the relation between depression and labor participation and alternatively the cost associated with that illness. Most of the early literature treated health and health deterioration as exogenous to labor participation decision. When the possible endogeneity of mental illness and participation is taken into account, there are significant decrements in employment, earnings, and hours of work for both men and women (Ettner and Kessler 1997; Ettner 2000). Thus, one of our worries is the issue of reverse causality, and in that sense there are a few studies which mainly using instrumental variables, such as Ettner et al. (1997) which used parental history of mental disorders as instrument for own mental disorder. In the same way, Alexandre and French (2001) used variables associated with religion as instrument for the mental disorder and they showed that depression implied a reduction in the probability of being employed by about a 19%.

Referring to the literature treating the endogeneity problem, most of the articles are based in variants of linear probability models to estimate nonlinear relationships using two stage estimation methods. An additional difficulty is the presence of a dummy endogenous regressor in binary choice models with panel data, then the standard two-stage method leads to inconsistent estimates. There are much fewer results available on discrete choice models with panel data and the majority of them are based on the study of the effect of fertility on labor supply. Random effects models with strictly exogenous variables have been considered by Chamberlain (1980, 1984) and Newey (1994). On the other hand, other studies had considered a fixed effects specification and also left the distribution of the effects unrestricted. Some of them are the maximum score method proposed by Manski (1987) and the models proposed by Honoré and Lewbel (2002). Arellano and Carrasco (2003) considered a non parametric conditional expectation of the individual effects given the predetermined variables, but are otherwise parametric.

Unfortunately, the majority of the existing literature has still strict assumptions, mainly about the normal ditribution of the composite errors that we will try to relax. The hypothesis we want to contrast firstly is that depression is associated negatively with labor participation decisions. This paper makes some contributions to the previous literature on depression and labor supply; first we use microdata form SHARE, which is one of the most new and complete database related with health and disabilities. Second, the presence of a dummy endogenous regressor in a model with binary outcome makes our analysis different from the usual, which accounts for continuous endogenous regressors. In this paper, we show new empirical evidence of the effect of a mental illness on labor supply for the Spanish population separating the men and women. Firstly, we present a bivariate probit for panel data and then we complete it with a more general model, the switching probit with endogenous switching. Finally we discuss the possibility of propose a more flexible method which allows to carry out correct inference suppressing some of previous assumptions.

This article provides evidence of links between depression and labor market decisions and is presented as follows; Firstly, we discuss the determinants of depressive people and their consequently labor decisions. Then a review of the literature related to depression and labor market is presented which is followed by a descriptive analysis of the current situation of people with depression in labor market. Consequently, we proposed several models that allow to quantify the effect of having depression on employment decisions, finally the results and conclusions from the study are exposed.

2 Model and Estimators

The purpose of this paper is to estimate the causal effect of depression on labor participation, given that depression is not exogenous to labor decisions. To this end, we define y_i^* as the latent process that explains labor participation decision for individual i. Then, the model can be written like that:

$$y_i^* = \alpha_0 + \beta_1 x_i + \delta d_i + \beta_2 x_i d_i + \epsilon_i. \tag{1}$$

Where x_i are exogenous characteristics of individuals, d_i is the variable indicating the onset of the depression and ϵ_i is the error term. Before the estimation we have to highlight the difficulties of giving a value to the effect of depression on labor market decisions; that problem is related to causality, because is possible the relation between those variables be in the opposite side (employment factors, such as the working hours can affect depression). Additionally the relation between depression and labor market decisions may be confounded by an unobserved factor influencing both variables. Otherwise, the variable y_i^* is not observable, we only observe a binary variable which indicates the participation outcome for person i, and it is defined as:

$$y_i = 1(y_i^* > 0) = 1(\alpha_0 + \beta_1 x_i + \delta d_i + \beta_2 x_i d_i + \epsilon_i \geq 0). \tag{2}$$

Where 1 is an indicator function. Firstly, if $\epsilon i|x_i, d_i \sim N(0, 1)$, then we had the standard probit model. In case that d were an endogenous variable and we had a valid instrument, z, and we know that: $d|x, z \sim N(\mu_d(x, z), \sigma_d^2)$, the parameters of this model could be easily estimated using two-stage method. But in our study, d is a dummy variable, so its distribution cannot be normal. In that case two-stage or instrumental variable methods are not appropriated.

One solution is to propose a way of dealing with both variables simultaneously, allowing for a correlation between the error term of the two equations, for recognizing that there may be characteristics that influence both the employment outcome and the depression. Basically there are three reason for the possible correlation between the labor participation and the onset of depression;

- A causal relation due to the effect of depression on participation, through the parameter δ.
- The participation and the depression may depend on other correlated observed variables x.
- The participation and the depression may depend on other correlated unobserved variables ϵ, u.

According to that, we specify a reduced form probit for depression:

$$d_i = 1(d_i^* > 0) = 1(\lambda_0 + \lambda_1 x_i + \lambda_2 z_i + u_i > 0). \tag{3}$$

Where u_i and ϵ_i are assumed to be jointly normally distributed and z is a variable that affects y only through d. To measure the effect of the depression in our model, holding x_i and ϵ_i constant, it is useful define the latent binary variables:

$$y_{i0} = 1(y_{i0}^* \geq 0) = 1(\alpha_0 + x_i\beta_1 + \epsilon_i \geq 0).$$

$$y_{i1} = 1(y_{i1}^* \geq 0) = 1((\alpha_0 + \delta) + (\beta_1 + \beta_2)x_i + \epsilon_i \geq 0). \tag{4}$$

The variable y_{i0} indicates the outcome if person i not have depression; $y_{i0} = 0$ if this person would not participate, and $y_{i0} = 1$ otherwise. In the same way, y_{i1} is the outcome associated with having depression. We know that both outcomes are incompatible and only one is observed. Also we appreciate that de difference $y_{i1} - y_{i0}$ is the effect of having depression for person i. That difference measures how the participation outcome vary with depression if the latter were not self-selected but were, instead exogenously determined.

As in Carrasco (2001), given the case when $\beta_1 < 0$, $\beta_2 < 0$, $\alpha_0 < 0$ and $\delta < 0$, the pair (y_{i0}, y_{i1}) may take on the values $(0, 0)$, $(1, 1)$ and $(1, 0)$, but this model rules out the outcome $(0, 1)$; that is when a person who was not working not having depression could start working when he/she suffer depression. A generalization of the previous model that allows the possibility of the outcome $(0, 1)$ can be obtained considering two different error terms, then:

$$y_{i0} = 1(y_{i0}^* \geq 0) = 1(\alpha_0 + x_i\beta_1 + \epsilon_{1i} \geq 0).$$

$$y_{i1} = 1(y_{i1}^* \geq 0) = 1((\alpha_0 + \delta) + (\beta_1 + \beta_2)x_i + \epsilon_{2i} \geq 0). \tag{5}$$

As before, we can define the participation outcome as;

$$y_i = y_{i0}(1 - d_i) + y_{i1}d_i. \tag{6}$$

Supposing that the error terms are jointly normally distributed with zero mean and covariance matrix, ω;

$$\omega = \begin{bmatrix} 1 & \rho_{01} & \rho_{0u} \\ & 1 & \rho_{1u} \\ & & 1 \end{bmatrix} \tag{7}$$

This model does not impose restrictions on the covariance matrix of $(\epsilon_i 0, \epsilon_i 1, u_i)$ and is like the one proposed by Manski et al. (1992). The standard bivariate probit is a special case of this in the case when $\rho_{0u} = \rho_{1u}$.This model can be consistent and asymptotically efficient estimated by maximum likelihood;

$$L_i(\alpha, \beta_1, \beta_2, \delta, \lambda_1, \lambda_2 | y_i, d_i, x_i, z_i) = Pr(y_i, d_i | x_i, z_i) = Pr(y_i | d_i, x_i) Pr(d_i | x_i, z_i). \tag{8}$$

3 Data

The Survey of Health, Ageing and Retirement in Europe (SHARE) is a micro database, longitudinal about health, socioeconomic status and social issues. This survey aims to build a European panel based on health and socio-economic issues which have relation with the ageing process. It covers more than 85,000 individuals aged 50 or older from 19 European countries (+ Israel). This is a great tool to analyze the relations between health and labor force participation among Europe, as is our goal. SHARE is harmonized with the Health and Retirement Study (HRS) of the United States and the Longitudinal Study of Ageing (ELSA) from the UK, and is now at the center of a network of longitudinal surveys on aging. Its power is due to the panel structure which allows for taking into consideration the dynamic character of ageing and helps to identify individual transitions. SHARE started in 2002 and then the first wave was related to 2004 for 11 countries, it has been extended to 15 countries in the second wave, it returned to 13 in the third wave and finally there are 19 in the fourth.

We select observations which have available information for the four waves of the survey in order to have the most complete information about our variables of interest. Our sample has a size of 29.275 observation but some of the variables have missing values, that is the reason because in some cases we have less observations.

Table 1: Definition of variables.

	Definition
Working hours	Hours worked per week
Female	1 if female
Age	Age in years
Education	Number of years of education
Children	number of children
Depression	1 if the person declares to have depression
CASP	Value that the person takes in the scale of quality of live
Obese	1 if the person is obese
partner	1 if the person lives with a partner

Source: SHARE.

4 Results

Desciptive statistics for the main set of chosen variables, are showed in table 2. The 57% of the sample were women, and the mean age was 57 years old. Depression is really significant, the 38% of the respondents declared to have it. In the sample the mean of years studing was 11 and the 20% were obese.

Table 2: Descriptive Statistics.

	Obs.	**Mean**	**Standard deviation**	**Min.**	**Max.**
Working hours	33984	37,38	14,44	0	168
Female	80497	0,57	0,49	0	1
Age	80503	57,29	4,84	24	65
Education (years)	71488	11,40	4,16	0	25
Children	66750	2,15	1,34	0	17
Depression	66218	0,38	0,48	0	1
CASP	58342	37,78	5,97	12	48
Obese	64939	0,20	0,40	0	1
Partner	80470	0,81	0,38	0	1

Source: SHARE.

Table 3: Labor indicators by the onset of depression. Percentages

	Employed	**Retired**	**Unemployed**	**Incapacity**	**Homemaker**
People with depression	21,36	51,7	3,13	4,05	18,77
People without depression	26,6	56,07	2,35	2,45	11,76

Differences in labor participation between people with or without depression are exposed in table 3. The employment rate is lower having depression and also the retirement rate. In the opposite side, the unemployment rate, the incapacity proportion and homemaker are higher for those suffering this illness.

4.1 Simultaneous estimation

We now present empirical evidence of the model exposed above, and test that depression affects negatively the labor participation. Then, in table 4 the results obtained from the bivariate estimation are presented.

Table 4: Bivariate probit regression. Spanish women

	Employed	**Depression**	**Marginal effect (employed;depression)**	**X**
Age	-0,056***	-0,016***	-0,011	56,30
Education	0,06***	0,01***	0,008	9,07
Children	-0,05**	0,001	-0,009	2,30
CASP	0,026***	-0,086***	-0,006	36,66
Partner	-0,32***	-0,217***	-0,090	0,86
Obese		-0,072***	-0,0003	0,23
Constant	1,52***	4,33***		
Artrho	-0,07**			

Likelihood-ratio test of rho=0: chi2(1) = 2,93	Prob > chi2 = 0.08
Sample	1520

*** Significance at 1% level, **Significance at 5% level and * Significance at 10% level.

The age decreases the probability of having a job for Spanish women. Age has also a negative effect in the onset of depression. More educated women have more probability of being employed buy also of suffering from depression. Women who have children are less prone to be employed whereas they have less probability of suffering depression. Women who lives with a partner have less probability to participate in labor market and also to suffer depression. Obese women have a negative association with the probability of having depression. Finally as we hoped, to have better quality of life increases the probability of employment and in addition it reduces the probability of depression.

This model show a significative relation with negative sign between employment and depression. The correlation coefficient between bivariate outcomes is $-0,07$ and it is significant, therefore the joint estimation is preferable than the separate estimation of two probit models, because the decisions are related.

Table 5: Bivariate probit regression. Spanish Men

	Employed	**Depression**	**Marginal effect (employed;depression)**	**X**
Age	-0,102***	-0,003***	-0,010	57,43
Education	0,02***	-0,00	0,002	9,52
Children	-0,036	0,022	-0,000	2,06
CASP	0,069***	-0,080***	-0,007	37,78
Partner	0,416***	-0,222**	0,006	0,84
Obese		0,032*	0,005	0,21
Constant	3,03***	2,69***		
Artrho	-0,166***			

Likelihood-ratio test of rho=0: chi2(1) = 8,77	Prob > chi2 = 0.00
Sample	1142

*** Significance at 1% level, **Significance at 5% level and * Significance at 10% level.

Analyzing the case of men, we can observe that the age decreases the probability of having a job and also the probability of depression. Men who are more educated have more probability of being employed and are less prone of suffering from depression although the latter is not significant. Men who have children are less prone to be employed but in this case this is not significant. Men who are living with a partner have more probability to participate in labor market but less probability to suffer depression. Obese men have a positive association with the probability of having depression. Finally as it was expected, to have better quality of life increases the probability of employment and in addition it reduces the probability of depression.

This model show a significative relation with negative sign between employment and depression. The correlation coefficient between bivariate outcomes is $-0,08$ and it is significant, therefore the joint estimation is preferable than the separate estimation of two probit models, because the decisions are related.

As it is shown in table 6, the predictive power of the model is encouraging.

Table 6: Predictions of the model

	Predicted Mean	**Predicted Std.Dev.**
Pr(Employed=1) Women	0,324	0,181
Pr(Depression=1)Women	0,478	0,192
Pr(Employed=1) Men	0,590	0,224
Pr(Depression=1) Men	0,258	0,146
	Sample Mean	**Sample Std.Dev.**
Pr(Employed=1) Women	0,315	0,464
Pr(Depression=1)Women	0,469	0,499
Pr(Employed=1) Men	0,577	0,494
Pr(Depression=1) Men	0,247	0,431

	Predicted Mean	**Predicted Std.Dev.**
Pr(Employed=1,Depresion=1) Women	0,142	0,082
Pr(Employed=1,Depresion=0) Women	0,230	0,132
Pr(Employed=0,Depresion=1) Women	0,291	0,165
Pr(Employed=0,Depresion=0) Women	0,335	0,133
Pr(Employed=1,Depresion=1) Men	0,120	0,065
Pr(Employed=1,Depresion=0) Men	0,487	0,220
Pr(Employed=0,Depresion=1) Men	0,142	0,141
Pr(Employed=0,Depresion=0) Men	0,249	0,127

4.2 Approach of Switching Probit Models for Panel Data

Additionally, in order to estimate the relationship between two endogenous discrete variables with the special considerations of panel data, is possible to follow the approach of Arellano and Carrasco (2003). Then, considering N individuals who are observed T consecutive time periods, we can model labor participation as:

$$y_{it0} = 1(\gamma_0 + \beta_0 x_{it} + \xi_{it0} \geq 0). \qquad d_{it} = 0.$$

$$y_{it1} = 1(\gamma_1 + \beta_1 x_{it} + \xi_{it1} \geq 0). \qquad d_{it} = 1. \tag{9}$$

Where $\xi_{itj} = \eta_i + v_{itj}, \qquad j = 0, 1$. And the reduced equation for the depression is:

$$d_{it} = 1(\lambda_0 + \lambda_1 x_{it} + \lambda_2 z_{it} + u_{it} \geq 0). \tag{10}$$

Now, we allow for an unobserved effect in the depression equation, provided that u_{it} are allowed to be serially correlated. Let us to define; $w_{it} = (z_{it}, x_{it}, y_{i(t-1)}, d_{i(t-1)})$. We assume that the error terms have a normal distribution given w_i^t of the form:

$$\begin{bmatrix} \xi_{it0}|w_i^t \\ \xi_{it1}|w_i^t \\ \epsilon_{it}|w_i^t \end{bmatrix} \sim N(\begin{bmatrix} (E(\eta_i|w_i^t) \\ (E(\eta_i|w_i^t) \\ 0 \end{bmatrix}, \omega_t). \tag{11}$$

Where;

$$\omega_t = \begin{bmatrix} 1 & \rho_{01} & \rho_{0u_t} \\ & 1 & \rho_{1u_t} \\ & & 1 \end{bmatrix}. \tag{12}$$

The resulting model could be seen as a member of the class of random-effects models, since the individual effects are treated as random variables. Moreover, in the model the individual effects have a distribution which is not specified and additionally, η_i and v_{it} are not required to be conditionally independent. Furthermore dependence between the explanatory variables and the individual effects is allowed because of the conditional mean of the latter given the observed path of w. Moreover, the regressors can be predetermined, that is, x_{it} and z_{it} do not depend on present or future values of v_{it} but may be relation between lagged values of v and x, z. Then;

$$y_{it0} = 1(\gamma_0 + \beta_0 x_{it} + E(\eta_i|w_i^t) + u_{it0} > 0). \qquad if \quad d_{it} = 0.$$

$$y_{it1} = 1(\gamma_1 + \beta_1 x_{it} + E(\eta_i|w_i^t) + u_{it1} \geq 0). \qquad d_{it} = 1. \tag{13}$$

Where $u_{itj} = \xi_{itj} - E(\eta_i|w_i^t), \qquad j = 0, 1.$

The variable η_i is unobserved and its forecast is modified each period according to the information accumulated. The specification is based on the assumption that the demeaned errors $\xi_{itj} - E(\eta_i|w_i^t)$ have a distribution which can change with t but which is independent of w_i^t. Since w_i^t possibly affect the shape of the conditional distributions $\eta_i|w_i^t$, this assumption implies that in general v_{itj} will only be independent of w_i^t, which is a limitation of this approach (For more details see Carrasco, 2001).

In order to carry out this estimation we could deal with two possibilities;

1. When we have discrete random variables.
2. When we have continuous random variables.

In the first case, if we have discrete random variables with finite support of J mass points (for example, two mass points). Then, the vector w_i^t will have a finite support of 2^4 points given by $(\phi_1, ..., \phi_{2^4})$, so the vector w_i^t takes on $(2^4)^t$ different values $\phi_j^t (j = 1, ..., (2^4)^t)$. Thus;

$$\psi_j^t = E(\eta_i|w_i^t = \phi_j^t), \qquad j = 1, ..., (2^4)^t. \tag{14}$$

It is possible to use the law of iterated expectations as a way to link the parameters ψ_j^t, then,

$$\psi_j^{t-1} = \sum_{l=1}^{2^4} \psi_{(l-1)(2^4)^{t-1}+j} Pr(w_{it} = \phi_l | w_i^{t-1} = \phi_j^{t-1}), \qquad j = 1, ..., (2^4)^{t-1}; \qquad t = 2, ..., T. \tag{15}$$

On the other hand, since the model includes a constant term, it is not restrictive to assume $E(\eta_i) = 0$. Then;

$$E(\eta_i) = \sum_{l=1}^{2^4} E(\eta_i|wi1 = \phi_l) Pr(w_{i1} = \phi_l) = 0. \tag{16}$$

Thus, the initial probabilities, $p_l = Pr(w_{i1} = \phi_l)$ are left unrestricted, and just add 2^4 parameters to the full likelihood function of the data. The model can be estimated then by ML. Firstly we estimate jointly the parameters of interest $\gamma_0, \gamma_1, \beta_0, \beta_1, \lambda, \rho_{ou}, \rho_{1u}$ with the "nuisance" coefficients ψ_j^t. While the ψ_j^t have been solved recursively using the restrictions (14) and (15) as functions of ψ_j^T and the other parameters of the model. Then;

$$P_{it}^{00} = Pr(h_{it} = 0, d_{it} = 0) = \Phi(-\gamma_0 - \beta_0 x_{it} - \Psi_j^t, -\lambda z_{it}; \rho_{0u}).$$

$$P_{it}^{01} = Pr(h_{it} = 0, d_{it} = 1) = \Phi(-\gamma_1 - \beta_1 x_{it} - \Psi_j^t) - \Phi(-\gamma_1 - \beta_1 x_{it} - \Psi_j^t, -\lambda z_{it}; \rho_{1u}).$$

$$P_{it}^{10} = Pr(h_{it} = 1, d_{it} = 0) = \Phi(-\lambda z_{it}) - P_{it}^{00}).$$

$$P_{it}^{11} = Pr(h_{it} = 1, d_{it} = 1) = \Phi(\lambda z_{it}) - P_{it}^{01}). \tag{17}$$

Where;

$$\Psi_j^t = \sum_{j=1}^{(2^4)^t} \psi_j^t 1(w_i^t = \phi_j^t). \tag{18}$$

Secondly, in the case of continuous variables, estimation cannot based on cell sample frequencies. Then, let us define the variables:

$$d_{it}^t = 1(w_i^t = \phi_j^t) \tag{19}$$

And

$$h_t(w_i^t) = \sum_{j=1}^{(2J)^t} d_{ij}^t p_{tj}. \tag{20}$$

Now, we rely on non-parametric smoothed estimators of the reduced form probabilities $h_t(w_i^t)$ in order to construct ortogonality conditions. Another aspect here, is that with a continuous x_{it} it is feasible to estimate non-parametrically the distributions of the composite errors for each t.

The $tx1$ random vector $y_0^{t-1} y_{i0}, y_{i1}, ..., y_{i(t-1)}$ has a multivariate Bernoulli distribution, and takes on 2^t different values $\zeta_j^{t-1}(j = 1, ..., 2^t)$. Therefore we consider non-parametric estimates of $h_t(w_i^t)$ of the form:

$$\tilde{h_t}(w_i^t) = \sum_{j=1}^{2^t} \tilde{h_{tj}}(x_i^t) 1(y_i^{t-1} = \zeta_j^{t-1}). \tag{21}$$

Where $\tilde{h_{tj}}(x_i^t)$ is a non-parametric smooth (e.g Kernel) estimator of the conditional probability.

$$h_{tj}(x_i^t) = Pr(y_{it} = 1 | x_i^t, y_i^{t-1} = \zeta_j^{t-1}). \tag{22}$$

We are working in new methods based on the study of Arellano and Carrasco (2003) but relaxing some of their distributional assumptions. In our concrete case, to deal with endogenity of depression in labor decisions.

5 Conclusions

The analysis of this paper suggests that the study of differences in labor participation decisions are affected for the onset of depression. We analysis different methods to arrive robust conclusions about the effect of a concrete illness such as depression has in labor decisions. Our results provide very valuable additional information beyond that disease that should be taken into account for studying the economical cost of it in relation with absinthism. We have also presented the results for an approximation of a binary model with an endogenous regressor which is also binary. From our application we show the importance of taking into account endogeneity of binary variables.

We show the results for a sample corresponding Spain desegregated by gender. There are some variations in the estimated quantities but are reasonable and following the same direction except for the variable "living with a parter" which is positively associated with labor participation for men but not for women. Focusing in depression, we conclude that this illness which is increasing significantly in recent years has a negative effect in labor market decisions. People suffering from depression has a low participation ratio preferring not to work or work less hours. So that, there exist a quantifiable cost of the depression; Firstly for the individual according to wages losses and also for the society in medical and social cost derived from it. Economical and Social Policies destined to prevent depression or also for learning to live with it and try to overcome this illness should be implemented. As we said, the consequences of prevention and efficient treatment could be significant not only in economical terms but also in quality of life.

6 References

Arellano, M. and Carrasco, R. (2003). Binary choice panel data models with predetermined variables. Journal of Econometrics, vol. 115(1): 125-157.

Alegría M., Chatterji P, Wells K, Cao Z, Chen CN, Takeuchi D and Jackson J, Meng XL (2008).Disparity in depression treatment among racial and ethnic minority populations in the United States. Psychiatr Serv., 59(11):1264-72.

Alexandre P. and French M. (2001). Labor Supply of Poor Residents in Metropolitan Miami, Florida. The Role of Depression and the Co-Morbid Effects of Substance Abuse. Journal of Mental Health Policy Economics ;4:16173.

Barrett GF. (2002). The effect of alcohol consumption on earnings. The Economic Record, 78:7996.

Becker, G. (1964). Human capital. New York: Columbia university press.

Carrasco, R. (2001). Binary Choice with Binary Endogenous Regressors in Panel Data: Estimating the Effect of Fertility on Female Labor Participation. Journal of Business and Economic Statistics, vol. 19(4):385-94.

Currie, J. (2009). Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. Journal of Economic Literature, American Economic Association, 47(1): 87-122.

Deaton, A. and Paxson, C. (1998). Health, Income, and Inequality over the Life Cycle. NBER Chapters in: Frontiers in the Economics of Aging, 431-462. National Bureau of Economic Research.

Duque-Gonzlez, B. (2009). The socioeconomic costs of mental illness in Spain. European Journal of Health Economics, 10 (4):361-369.

Ettner, S.L. (1996). The opportunity costs of elder care. Journal of Human Resources, 31:189-205.

Frank, R. and Gertler, P. (1991). An assessment of measurement error bias for estimating the effect of mental distress on income. Journal of human resources. 26(1):154-164.

Franco, M., Sanmartin, A., Guija, J.A. and Giles, E.(2003). Difficulties in the evaluation of affective disorders in eldery people. Revista de Psicogeriatría, 3(1),:12-16.

Heckman, J.(2001). Accounting for Heterogeneity, Diversity and General Equilibrium in Evaluating Social Programmes. Economic Journal, Royal Economic Society, 111(475), 654-99.

Honore, B. and Lewbel,A. (2002). Semiparametric Binary Choice Panel Data Models Without Strictly Exogeneous Regressors. Econometrica, Econometric Society, vol. 70(5):2053-2063.

King M, Semlyen J, See Tai S, Killaspy H, Osborn D, Popelyuk D, Nazareth I. (2008), A systematic review of mental disorder, suicide, and deliberate self harm in lesbian, gay and bisexual people: a systematic review. BMC Psychiatry. 8:70

Maddala, G. (1983), Limited-Dependent and Qualitative Variables. Economics, New York: Cambridge University Press: 257-291.

Manski, C. (1987), Semiparametric Analysis of Random Effects Linear Models from Binary Panel Data. Econometrica, Econometric Society, vol. 55(2):357-62.

Maes, M. (2002). Effects of age and gender on the classification and phenomenology of unipolar depression. Acta Neuropsychiatrica, 14:29-35.

McNeil, J.K., and Harsany, M. (1989). An age difference view of depression. Canadian Psychology, 30:608-615.

Mincer, J. and Polacheck, S. (1974). Family investments in human capital: Earnings of women. Journal of Political Economy, 82:76-108.

Newey, W. (1994). The asymptotic variance of semiparametric estimators. Econometrica, Econometric Society, vol. 62 (6):1349-1382.

Sharp, L.K. and Lipsky, M.S. (2002). Screening for depression across the lifespan: a review of measures for use in primary care settings. American Family Physician, 66(6):1001-1008.

Stage, K.B., Bech, P., Kragh-Sorensen, P., Nair, N.P. and Katona, C. (2001). Differences in symptomatology and diagnostic profile in younger and elderly depressed inpatients. Journal of Affective Disorders, 64(2-3):239-248.