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APPLIED ECONOMETRICS AND FORECASTING

MASTER´S FINAL WORK

DISSERTATION

ANALYSIS OF POVERTY AND SOCIAL EXCLUSION WITH PANEL MICRODATA

JOSÉ MIGUEL RAMOS MODESTO

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Abstract

This dissertation intends to model the dynamics of social exclusion by investigating the individual characteristics that contributes to increase the probability of being socially excluded, as well as the identification of the most vulnerable population groups.

We will be using the criteria proposed by the Eurostat to define social exclusion, and we will be using a four years longitudinal data from European Statistics on Income and Living Conditions relative to the Portuguese population. We aggregate the criteria into a binary indicator of social exclusion, so we will be applying a Pooled Probit and a Random Effects Probit model to the data.

This work also intends to enrich the literature about this subject, as we were able to reach interesting results, relative to the determinants of social exclusion and some of the most vulnerable groups to this phenomenon.

Keywords: *Social Exclusion, Panel Data, Probit, Poverty, Material Deprivation, Low Work Intensity, Unemployment, Vulnerability, Social Disadvantage, SILC*

Resumo

Esta dissertação propõe-se a modelar a dinâmica da exclusão social ao investigar as características dos indivíduos que contribuem para aumentar a probabilidade deste se encontrar em situação de exclusão social, assim como identificar os grupos mais vulneráveis.

Para o efeito, vamos usar o critério proposto pelo Eurostat para definir a exclusão social, usando uma base de dados longitudinal de quatro anos do ICOR (Inquérito para as Condições de Vida e Rendimento) relativa à população portuguesa. O critério é traduzido num indicador binário de exclusão social, assim sendo, recorremos aos modelos Pooled Probit e Probit de Efeitos Aleatórios para modelar os nossos dados.

Este trabalho tem também como objetivo enriquecer a literatura existente acerca desta matéria, e possibilitou-nos alcançar resultados interessantes, relativos às características que ajudam a explicar a probabilidade de ocorrência de exclusão social e aos grupos que se mostram mais vulneráveis a este problema.

Palavras-chave: *Exclusão Social, Dados em Painel, Probit, Pobreza, Privação Material, Baixa Intensidade Laboral, Desemprego, Vulnerabilidade, Desvantagens Sociais, ICOR*

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I. Introduction

Social exclusion represents a major challenge in todays' society. It can prevent the individual from participate in many aspects of life in society, degrading life expectations, social cohesion, and thus, decreasing the sense of belonging to the community and compromising economic prosperity. Measuring social exclusion is also a challenge, since it can be describe as a multidimensional and dynamic process, and there is no consensus on a formal threshold. This work will present some of the different definitions adopted by several investigators, but will formally stand for the Eurostat definition when analysing the data and applying an econometric model to it. Econometric methods have been popular in conducting studies on social exclusion, due to the robustness and consistency of its results, as well as its success in translating the dynamics towards the process of social exclusion.

This works aims to contribute to a more enlightment about the social exclusion reality, its determinants, who are the most vulnerable and seeks to explain which variables contribute to a higher propensity of experiencing social exclusion. The higher concern about this subject is motivated by the Europe 2020 strategy, which propose to diminish the number of European Union citizens socially excluded by 20 million, strengthening the European society for the challenges of the next decades. Schienstock *et al.* (1999) explores the challenges brought by the new social structures of the Information Society, one of them being the risk of increasing the prevalence of social exclusion among population.

In this dissertation we will be analysing the Portuguese reality, which is known to be one of the most unequal societies within the European Union.

II. Background

Several authors have been paying attention to social exclusion for the past few years, due to the challenges that it generates to society and public decisors. At this point, we see the necessity to explore some studies that have been made within this subject, to briefly summarize the main conclusions.

i. Definition of Social Exclusion

Contrarily to other social issues, such as poverty, it has not been identified a formal social exclusion threshold (Silver, 2007). Moreover, different authors frequently presents different definitions. Poggi (2003), stating Lee-Murie (1999), defines social exclusion as a process that excludes individuals from social, economic and cultural networks, and which has been linked to the idea of citizenship. Silver (2007) gives a more precise definition, defining social exclusion as a rupture of social relations, institutions, social cohesion, integration or solidarity. Tsakloglou and Papadopoulos (2002) stating Silver (1994), de Haan (1998) and Byrne (1999), says that social excluded individuals are those unable to exercise social, political and civil rights or to participate on a diversity aspects of life in society. Additionally, stating Mayes *et al.* (2001) and Atkinson *et al.* (2002), they also interpret social exclusion as exclusion from the labour market and material deprivation. In the same article they suggest social exclusion to be a chronic cumulative disadvantage. According to D'Ambrosio and Chakravarty (2003), the European Commission's Programme specification for 'targeted socioeconomic research' defines social exclusion as the disintegration and fragmentation of social relations, and thus, as a process leading to cumulative disadvantages of various forms. These are just some examples of the diversity of suggestions for the definition of social exclusion.

A conclusion we can extract from these, and which is frequently mentioned among researchers, is that social exclusion is a multidimensional and dynamic process. Therefore, longitudinal data are the most widely used to investigate this phenomenon.

For quantitative purposes of this work, we will consider an individual as social excluded using the Eurostat criteria, which is standing for at least one of the following three dimensions: at risk of poverty[1], material deprivation[2], or living in a household with a very low work intensity[3].

ii. Econometric approaches

Many approaches were followed by many authors for them to reach their conclusions, and many were the aspects considered. Poggi (2007) states that we can have true state of dependence (where the probability of being socially excluded in the future depends of whether or not the individual already experienced it in the past), observed characteristics (such as scholarship, gender, parenthood, and others) and unobserved heterogeneity (the characteristics which can not be observed or measured and are inherent to the individual, i.e., are constant in time). Poggi estimates a dynamic random effects logit model with both lagged dependent and exogenous variable, in which the dependent variable is an indicator that can assume the value of one if exclusion occurs, and zero

[1] A person is said to be at risk of poverty if he or she is below the at-risk-of-poverty threshold, which is set at 60 % of the median income per adult equivalent after social transfers
[2] A person is said to be materially deprived if he or she can not afford at least three out of a list of nine items established by the social protection committee
[3] A household with very low work intensity is defined as a household where the members worked less than 20 % of their total potential during the reference year

otherwise. Another methodological aspect is that Poggi considers an individual as being excluded if the individual is, at least, excluded in one dimension among eight[4]. Some of the author's main conclusions is the strong presence of a true state dependence, that being lone parent or less educated seems to raise significantly the probability of being socially excluded, and that the region where the individual lives also appears to be important to explain social exclusion. Another interesting idea is that social exclusion, through the introduction of year dummies, seems to decrease over time.

Tsakloglou and Papadopoulos (2002) have an interesting suggestion, analysing the high risk of social exclusion trough several European countries, and highlighting the differences among them. For usage in statistic (and econometrics) aspects, they consider at high risk of social exclusion those who are deprived in at least two, among four, deprivation indicators, being these lack of income (also known as poverty), living conditions, necessities of living, and social relations. One interesting result, is that we can find higher rates of population in high risk of social exclusion in poorer countries according to the first three criteria, but not to the fourth. They also look for individual characteristics that may help explain the probability of being in high risk of social exclusion. One interesting idea, is besides measuring for the individual self-characteristics, they go for the characteristics of the reference person of the individual's household. They do this using a logistic regression, and find that the 'effects associated with educational qualifications of the household's reference person are stronger than those associated with the educational qualifications of the individual'. Other results shows that lack of full-employment, low educational qualifications, lone parenthood, non-EU

[4] These dimensions are "the basic need fulfilment", "living in a safe and clean environment", "having an adequate income", "being healthy", "to reach a certain quality of life", "to have an adequate house", "the ability to have social relationships", and "being able to perform a paid, or unpaid, work activity".

citizenship and bad health are associated with increased risk of social exclusion, and qualifying countries in groups according to their type of welfare regime allows to see here statistical significance also. It was even possible to conclude that in several ways, the country where the individual is from, impacts the probability of being at high risk of social exclusion due to a specific individual characteristic. For example, elderly people have an increased high risk of social exclusion in some southern countries, but a reduced risk in some northern countries. This results advice for, being the reality among European countries very different, the problem of social exclusion shall have different approaches.

All the previous authors talked about and showed results estimated for lone parenthood. Heavily related to social exclusion is early motherhood as well, and Hobcraft and Kiernan (2001) explored deeply the questions associated to this phenomenon. They divided a population of women in four categories, those who were mothers for the first time under age 20, between 20 and 22, 23 to 32 and those who were not mothers at age 33. In a first stage, they control for eleven variables representing different outcomes in adult life (such as ill-health and social housing), and found high correlation between all these variables and early motherhood. After that, they tested for child poverty (and other factors, such as contact with police by age 16), and to do so, they applied a logistic regression. One of the main conclusions, is that adverse adult outcomes are more significantly more probable to occur for those who enter motherhood early, and that having experienced child poverty increases the chances of becoming an early mother. One interesting idea is that this can also suggest the concept of true state of dependence. Thus, poverty has been closely linked to social exclusion several times. Bradshaw *et al.* (2000) identifies three different measures of poverty – Income poverty, lack of socially perceived necessities (lack of items that were considered as necessities by the general population) and subjective poverty (people that considers themselves poor) – and three different dimensions of social exclusion – exclusion from the labour market, exclusion from basic services and exclusion from social relations – and in a sample of 1200 households of the British population, they find that between those who are excluded in at least one dimension, 19% are income poor. They also find that those who are excluded from the labour market, 53% are income poor. This seems to indicate a fair relationship between poverty and unemployment, but also means that social exclusion affects a significant proportion of people that is not poor. However, through a set of logistic regressions, they find a strong association between poverty and social exclusion, and that (and again) lone parenthood, households in social housing and with income support are the most likely to be poor and also socially excluded. Gallie *et al.* (2003) explored how labour market exclusion leads to poverty and social exclusion. They stated that this reinforce the risk of long-term unemployment, which means that there can be a vicious circle of social exclusion (remember the concept of true state dependence of Poggi (2007)). Unemployment can cause significant deprivation and financial difficulties, which can make more difficult for people to participate in activities in the community, increasing social isolation that may reinforce labour market marginalization by restricting people from information about job offers and key social contacts. Gallie *et al.* (2003), to reach their conclusions on this, identifies two phases of the spiral of disadvantages that defines this process. The first being analysing the social consequences of falling to unemployment, and the second being related to whether poverty or social exclusion brings more difficulty to get a new job. While finding evidence of linkage between poverty and unemployment, they found none for social exclusion. In fact, they find that experiencing multiple deprivation was not resulting from unemployment itself, but from becoming unemployed in specific social environments. On the second phase, they find that the unemployed who were poor took significantly more time to exit unemployment. So the main conclusion is the existence of a vicious circle between poverty and unemployment, with very little relation to social exclusion.

III. Data

As previously presented, in this work we are looking to explain social exclusion through individuals' and households' characteristics, investigating who are the most vulnerable groups, and analysing which characteristics contributes to that vulnerability.

We will be using longitudinal data from European Statistics on Income and Living Conditions, for the population living in the Portuguese territory, from years 2010 to 2013. This includes a diversity of information such as income, housing conditions, scholarship, presence in labour market, health, and so on.

After treating the information, the balanced panel comprehends 1049 households, with a total of 2010 individuals. Because of incomplete information provided by some individuals, which required us to exclude them from analysis, it is relevant to state that we might have a selection problem. Without excluding these individuals, we would have 1267 households with a total of 2584 individuals. When analysing the individuals we excluded from analysis, we observe some particular characteristics that differentiates them from the rest of the sample; only 2.87% of these individuals had tertiary education and 2.92% had secondary education, comparing to 12.06% and 15.42%, respectively, of those included in the analysis. The average age is also much higher, 62 years old against 50 years old. These numbers suggests that the individuals who provided incomplete information are mainly elderly or people with very low scholarship, who had some difficulty on completing the inquiry. This definitely represents a limitation on our analysis.

Following this, we were able to construct the social exclusion indicator. This indicates people who felt material deprivation, poverty risk or lived in a household with very low work intensity. One question we can bear in mind, is how do these different dimensions combine, and how severe can social exclusion be. Before trying to answer that question, we can look at the proportion of individuals experiencing social exclusion at each year in table VI on Appendix I. It might be relevant to keep in mind that during the period in analysis the Portuguese economy have been passing through a recession, which can deeply impact social conditions. We can see these numbers increasing from 27.66% in 2010, to 30.00% in 2013. Having a more deeply look at the social exclusion indicator composition, in table VII Appendix I, we can see how do the three different dimensions distribute between themselves; the majority of the individuals experiencing social exclusion stands for only one dimension, being material deprivation the more common, and living in a household with very low work intensity the less common. The share of both these two dimensions isolated increased during the period in analysis, whilst at risk of poverty alone decreases. It is an interesting observation because when looking at table VIII Appendix I, in fact the share of population at risk of poverty decreases among our sample. Trying to find an answer for this might be tricky, but one simple and reasonable explanation may be thinking about the poverty threshold. Unlike material deprivation and living in a household with very low work intensity, an individual being at risk of poverty is not an independent condition of what is happening with the other individuals, being the poverty threshold indexed to the median income of the population.

In fact, when looking at table IX Appendix I, the median income in our sample decreases 2.82% from 2010 to 2013. Another reasonable explanation, is that some people that were at risk of poverty alone on the beginning of the period in analysis, later on started to experiencing also one, or both, of the other two dimensions; table VII Appendix I shows us that people living in a household with very low work intensity and at risk of poverty increased, and people experiencing all three dimensions had a more significant increase. This also tell us that not only have social exclusion increased, its severity has also increased.

On table V Appendix I we can see the description for each variable we tested. The meaning of each variable is as follows: *exc* – our dependent variable, a dummy variable with value one if the individual is socially excluded according to the indicator we adopted, and zero otherwise; *sol*, *cas*, and *viuv* – dummy variables, with *sol* assuming value one if the individual is single and zero otherwise, *cas* assuming value one if the individual is married and zero otherwise, and *viuv* assuming value one if the individual is a widow or a widower (being the divorced and separated the reference group); *ter* and *sec* – dummy variables, with *ter* assuming value one if the individual has tertiary education and zero otherwise, and *sec* assuming value one if the individual has secondary education and zero otherwise (being the reference group those that have less than secondary education); *saude* and *ssaude* – dummy variables, with *saude* assuming value one if the individual considers his or her health status good or very good and zero otherwise and *ssaude* assuming value one if the individual considers his or her health status bad or very bad (being the reference group those who considers their health status fair); *moradia* – dummy variable with value one if the individual lives in a detached house and zero otherwise (being the individuals that do not live in a detached house the reference group); *prop*, *alojgrat* and *rendinf* – dummy variables, with *prop* assuming value one if the individual (or another member of the household) owns the residence in which he or she lives and zero otherwise, *alojgrat* assuming value one if the individual lives in an accommodation provided by someone else without any costs or provided by in exchange for a wage and zero otherwise, and *rendinf* assuming value one if the individual lives in a rented house with a supported rent (being the tenants without any supports the reference group); *den_p* and *frac_p* – dummy variables, with *den_p* assuming value one if the individual lives in a high density populated area and zero otherwise, and *frac_p* if the individual lives in a low density populated area (being those who live in a fair density populated area the reference group); *fem* – dummy variable with value one if the individual is a female and zero otherwise (males are the reference group); *fememp* – dummy variable with value one if the individual is an employed female and zero otherwise (being the reference group those who are male or unemployed or inactive female); *emp* and *desemp* – dummy variables, with *emp* assuming value one if the individual is employed and zero otherwise, and *desemp* assuming value one if the individual is unemployed and zero otherwise (being those who are inactive the reference group); *idade* – gives the age of the individual; *dmasc*, *uaumc*, *daudc* and *datcoo* – dummy variables, with *dmasc* assuming value one if the individual lives in a household with two or more adults without children and zero otherwise, *uaumc* assuming value one if the individual lives in a household with one adult and one or more children and zero otherwise, *daudc* assuming value one if the individual lives in a household with two adults and one or two children and zero otherwise, and *datcoo* assuming value one if the individual lives in a household with two adults and three or more children or more than two adults with at least one child (being the individuals living in households with one adult and without children the reference group); *cd* –

dummy variable with value one if the individual lives in a household with dependent children[5], and zero otherwise (being the individuals who lives in a household without dependent children the reference group).

The reason why we considered the employed females (*fememp*) is because, as we will see further, the female (*fem*) alone proved to not to be statistical significant, and we decided to search deeper for any evidence of gender inequality there might be, since it is well known the disadvantages that women can still face in work places nowadays, more than in general society. Matter of fact, the variable *fememp* showed to be statistical significant. We will have the opportunity to explore and discuss more the context and findings related to this later on.

For each of these variables, we can descriptive statistics on table IV Appendix I.

IV. Methodology

In this chapter we aim to describe the methodology adopted to reach our results. As mentioned before, several approaches were used in the past to study social exclusion, the phenomenon and the process itself, its implications as well the reality and the conditions that stimulate its growth. Tsakloglou and Papadopoulos (2002) presented results for the interesting idea that the determinants of social exclusion can vary between different countries in the European Union, which is a reasonable idea when we think of the importance of the family structure, the social relationships and the strength of the social institutions and politics, which can vary deeply between different cultures. In this paper

[5] The diference between children and dependent children, according to the Eurostat criteria, is that children are all those younger than 18 years old, and dependent children are the individuals younger than 25 years old and economically dependents.

we aim to explain the probability of experiencing social exclusion throughout the self-characteristics of the individuals in the Portuguese reality, on an attempt to reveal who are the most vulnerable groups.

Now, remember that social exclusion is not a binary concept, but instead a dynamic process that leads the individual to not participate in the society in many different ways and in many different levels, existing a combination of social forces, contributing to integrate the individual among us, or contributing to marginalize. Said this, we cannot measure *how much* an individual participate in society, but instead we observe if he or she is socially excluded according to the Eurostat criteria.

So, consider the following latent, not observed, variable model:

(1) $$y^{*} = (\text{social forces marginalizing}) - (\text{social forces integrating}) = (x\ \ \gamma + \varepsilon_1) - (x\ \ \delta + \varepsilon_2) = x\ \ \beta + \varepsilon$$

Where $x\ \ = (x_1, x_2, \ldots, x_p)$ is the vector of regressors, $\beta' = (\beta_1, \beta_2, \ldots, \beta_p)$ the vector of coefficients, and y^{*} is the level of participation in society.

And being y the binary indicator following Eurostat criteria such that:

(2) $$y\ \ = \begin{cases} 1, & y^{*} > 0 \\ 0, & \text{otherwise} \end{cases}$$

We are interesting in estimate the probability of an individual to be socially excluded according to the indicator we are following, so we can state:

(3) $$P(y = 1|x) = P(y^{*} > 0|x) = P(x\beta + \varepsilon > 0|x) = P(\varepsilon > -x\beta|x) = P(\varepsilon < x\beta|x) = G(x\beta)$$

With $G(x\beta)$ being the cumulative distribution function of $\varepsilon|x$, and a symmetric distribution. This cumulative distribution function, $G(x\beta)$, can assume various forms, but since we are considering the Probit model, we will specify a normal distributed form, *i.e.*, $\varepsilon|x \sim N(0,1)$ and equation (3) become

(4) $$P(y = 1|x) = \Phi(x\beta)$$

We will be using panel data, as it gives a richer analysis, so therefore, the models to be considered are the random effects Probit and the pooled Probit.

The random effects Probit can be written in the form:

(5) $$P(y_{it} = 1|x_{it}, c_i) = \Phi\left(x_{it}\,\beta + c_i\right), t = 1, \dots, T; i = 1, \dots, N$$

Where $x_{it} = (x_{it,1}, x_{it,2}, \dots, x_{it,p})$ is the vector of regressors, $\beta' = (\beta_1, \beta_2, \dots, \beta_p)$ the vector of coefficients and c_i being the individual unobserved heterogeneity. Unobserved heterogeneity are the characteristics inherent to the individual and constant in time, that we do not observe and that are correlated with the other variables. Since it is a relevant information that keeps omitted, the other variables present in the model becomes correlated with the error term. This is known as endogeneity and it is a violation of a basic assumption of the model, causing it to be biased.

Obviously, since we are considering more information than we do on the pooled Probit model (which ignores the unobserved heterogeneity), we can make more efficient estimations. Unfortunately, this comes with a cost. Random effects Probit model is only consistent when we specify the true density of the function, and it assumes that $c_i|x_i \sim \mathrm{Normal}(0, \sigma_c^2)$, which is a very strong assumption, since it implies that c_i has a normal distribution and that c_i and x_i are independent. Another strong assumption made by this model, is strict exogeneity. Considering that these assumptions are respected, the average partial effect for a continuous x_{tj} is $[\beta_j/(1 + \sigma_c^2)^{\frac{1}{2}}]\phi[x_t\beta/(1 + \sigma_c^2)^{\frac{1}{2}}]$, therefore we need to estimate $\beta_c = \beta/(1+\sigma_c^2)^{1/2}$. This can be done by maximizing the log-likelihood function, which can be written as:

$$(6) \quad \ln L(\beta, \sigma_c) = \sum_{i=1}^{N} \ln\left(\int \left[\prod_{t=1}^{T} \Phi\,(x_{it}\beta + c_i)^{y_{it}}[1 - \Phi(x_{it}\beta + c_i)]^{1-y_{it}}\right](1/\sigma_c)\phi(c_i/\sigma_c)dc_i\right)$$

And the average partial effects for a dummy x_{tk} is $n^{-1}\sum_{i=1}^{n}\{\Phi[\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_{k-1}x_{ik-1} + \beta_k(1)] - \Phi[\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_{k-1}x_{ik-1} + \beta_k(0)]\}$.

The alternative to this model leads us to the pooled Probit model. It can be written in the form:

$$(7) \qquad P(y_{it} = 1|x_{it}) = \Phi(x_{it}\beta), t = 1, \dots, T; i = 1, \dots, N$$

Again, $x_{it} = (x_{it,1}, x_{it,2}, \dots, x_{it,p})$ is the vector of regressors and $\beta' = (\beta_1, \beta_2, \dots, \beta_p)$ the vector of coefficients. A consistent estimator of β can be obtained by maximizing the partial log-likelihood function, which can be written as:

$$(8) \qquad \sum_{i=1}^{N}\sum_{t=1}^{T}[y_{it}\ln\Phi(x_{it}\beta) + (1 - y_{it})\ln[1 - \Phi(x_{it}\beta)]]$$

The pooled Probit estimator considers N independent observations, allowing for dependency on time. Furthermore, it only requires contemporary exogeneity, making it a more robust estimator than the random effects Probit, although less efficient.

When applying the pooled Probit estimator, it is recommended to use a cluster robust variance matrix (whose the cluster is the individual) to control for conditional correlation between y_{it} and y_{is}, with t≠s. The same practice is not recommended on a random effects Probit, because it needs to assume independence on time (strict exogeneity) to be consistent.

Looking at table II Appendix I we can see the estimated average partial effects with all regressors (many of them will not figure in our final model due to statistical insignificance) using random effects Probit and Pooled Probit, respectively. We can see that the results diverge significantly, so it is reasonable to assume that (and because pooled Probit is consistent in scenarios that random effects Probit is not) the conditions required by random effects Probit to be consistent are not satisfied, and therefore pooled Probit is much closer to the true values. This will be the estimator to use.

We shall also recall that endogeneity is a problem we might expect. Remembering the contributions made by Gallie *et al.* (2003) relative to the relations between social exclusion and unemployment, and between poverty and unemployment, they find the first one to be very insignificant, but very strong evidence for the second one. To think about this, we must keep in mind that we are using a different definition of social exclusion. While Gallie *et al.* (2003) define the degree of sociability according to household, informal social networks in the community, and associational participation, we stand for the Eurostat indicator, which looks into living in a household with very low work intensity, material deprivation, or poverty. Gallie *et al.* (2003) find evidence for a vicious circle between poverty and unemployment, which raises suspicion of it to be correlated to the unobserved heterogeneity. Thus, it seems reasonable to think that living in a household with very low work intensity can be a strong factor to long-term unemployment. To correct for endogeneity, we will be applying the Mundlak Device technic. It consists on adding the mean of each regressor across time (only those that vary in time, naturally) for each individual, replacing x_{it} with $(x_{it}, \bar{x}_i)$. We shall note that doing this to all regressors did not fit well to our model, so we will be doing that only to the regressor suspicious of being endogenous. With Mundlak we are assuming $c_i = \Psi_0 + \Psi_1 \bar{x}_i + a_i$, with $a_i | x_{it} \sim \mathrm{N}(0, \sigma_c^2)$ an thus, when we add $\bar{x}_i$ to our model we will have

$\Phi(x_{it}\beta + \bar{x}_i\xi)$. When we do this, and because we are adding a variable constant in time that only depends on the individual (which can be seen as a *fixed effect*), x_{it} will no longer be correlated with c_i.

After many statistical tests, we reach the final model, which we can see in table I Appendix I, alongside the other two models previously discussed. There we can see that all the variables are individually statistically significant at a 5% level, except variables *moradia* and *frac_p*, but these two are jointly statistically significant, at a 5% level also. To test this, we applied a likelihood-ratio test. To do so, we estimate the unrestricted model (with all the variables we previously defined) and a restricted model, with the same variables except those we are testing for, which is the same as imposing restrictions on the coefficients of those variables. This is the null hypothesis to be defended when testing, and under which the LR statistic is asymptotically chi-square distributed, with the degrees of freedom being equal to the number of restrictions being tested. So, the LR statistic is as follows:

(9) $$\mathrm{LR} = -2[\ln\mathrm{L}(\tilde{\theta}_{\mathrm{r}}) - \ln\mathrm{L}(\hat{\theta}_{\mathrm{ur}})]$$

Being $\mathrm{L}(\tilde{\theta}_{\mathrm{r}})$ the likelihood of the restricted model, and $\mathrm{L}(\hat{\theta}_{\mathrm{ur}})$ the likelihood of the unrestricted model. Of course, the likelihood of an unrestricted model will always be bigger than the likelihood of a restricted one (and thus the LR statistic will always assume a positive value). The higher the difference between the two log-likelihoods is, more evidence we have against the null hypothesis. We can see in table X Appendix I that the null hypothesis without restrictions on *moradia* and *frac_p* is the strongest one, so we opted to include those variables on the model and to not impose restrictions on them.

Said this, on the selected final model, the reference group for some variables changes. To know: for *cas*, the reference group is now unmarried people; for *prop* and *alojgrat* the reference group is now tenants; for *uaumc*, *daudc*, and *datcoo* the reference group are now the individuals living in households without children; for *frac_p* the reference group are now people that live in fair populated areas or highly populated areas; and for *desemp* the reference group is now both the inactive and the employed people.

V. Empirical Results

At this point, we are now able to do some interpretations. We can see the average partial effects associated to each variable on table III Appendix I, and thus make some considerations.

We find that married people have approximately less 11.5 percentage points of probability of being socially excluded than unmarried people. We can have a more deeply look on this in graph I Appendix II, which shows the distribution of this partial effect with a far more concentration of frequencies around -0.15, indicating that the effect is usually stronger than the average suggests. It is reasonable to say that married people often encounter more protection due to their partnership, and find conditions that stimulate more to reach a better outcome on social relationships. Similar results can be found relative to people having secondary and tertiary education. We estimate that people having secondary education have approximately less 11.6 p.p. of probability of being socially excluded than people with less than secondary education, and we estimate people having tertiary education to have even less percentage points, approximately 20.3 p.p.. Graphs II and III Appendix II appear to be similar, with a peak for the smallest values.

This definitely translates a major role on education, and it is easy to argue that people more educated find themselves more prepared to face difficulties and are more prepared to look for better opportunities. Also, people that consider their health status to be good or very good found to have approximately less 4.4 p.p. of probability of being socially excluded than those who consider their health status to be fair, while those who consider their health status to be bad or very bad have more p.p., approximately 11.3. Looking at graphs IV and V Appendix II, we see more concentration of frequencies around -0.06 and 0.14, respectively, indicating the partial effect usually to be stronger than the average suggests. This seems to suggest that poor health can represent an obstacle, in a sense that it can easily degrade quality of life, to reach better outcomes. It is reasonable to think that people with poorer health need to spend more resources on healthcare (either financial resources, time or energy) and find themselves less motivated due to a negative impact it is reasonable to expect having on life satisfaction. The effects relative to people living in detached houses are not significant (in spite of the fact it is jointly significant with another variable, which lead us to include it in the estimation). The effects relative to people living in scarcely populated areas have a similar behaviour, but this one is significant at a 10% level of significance, so it might worth some attention. People living in scarcely populated areas were estimated to perform worse than those who do not live in scarcely populated areas, having approximately more 2.6 p.p. of probability of being socially excluded than others. Looking at graph VII Appendix II, we see that we have more concentration of frequencies around 0.035. It is reasonable to think that people living in scarcely populated areas are more isolated from public services. Interesting results can also be shown for owners and people living in an accommodation provided by someone else without any costs or provided by in exchange for a wage. The owners are estimated to have approximately less 20.1 p.p of probability than tenants to be experiencing social exclusion, and people living in an accommodation provided by someone else without any costs or provided by in exchange for a wage have approximately less 7.2 p.p of probability of being socially excluded than tenants. We can see in graphs VIII and IX Appendix II that both variables have more concentration of frequencies on far left values. It is easy to understand what is happening to owners, since it is reasonable to think that owners, generally speaking, have a greater financial comfort since they are able to afford an accommodation of their own. The results relative to people living in an accommodation provided by someone else without any costs or provided by in exchange for a wage are more surprising. Two ways of trying to understand the reason, may lie in relation to the effectiveness of social policies, or that people whose employer provide accommodation have a more relevant occupation in a way it can provide better living conditions. Now, looking to employed females can be tricky, because we also have the variable relative to unemployed people. Therefore, we estimate that employed females have approximately less 13.1 p.p. of probability of being socially excluded than unemployed people (including other females), and approximately less 5.1 p.p. of probability than inactive people. A possible reason to this may be relative do gender inequality. We can think that, if females have to perform harder than males in most aspects of life (especially in the work place), it is reasonable to expect the difference in outcome between successful and unsuccessful females to be greater than the difference of outcome between successful and unsuccessful males, since the barriers are stronger for the first ones. Said this, graphs X and XI Appendix II can not be seen isolated from each other, but once again, we have more concentration of frequencies on absolute values. The results relative to the unemployed are the expected. It is to see that unemployed people usually get a worse outcome in life standards, and do not perform so well in social and (especially) professional relationships. The effects of age requires a more deep analysis, since it is our only continuous variable and we opted to include it in its quadratic form. We estimate that, in average, a one year older person will have approximately less 0.14 p.p. of probability of being socially excluded, but looking at graph XII Appendix II we can see this effect significantly changes. The partial effect starts to be largely positive at younger ages and starts decreasing, until the signal changes around 41-42 years old. This means that we estimate that between 16 and 41 years old, older people have an increased probability of being socially excluded, while between 42 and 80 years old we estimate that older people have a decreased probability of being socially excluded. Now, said this, we shall remind of the problems we faced on missing observations referred in section III. We have a selection problem, since we had to exclude from the data people that proved to be older and less educated, and hence, probably more vulnerable. The results relative to the households' composition are very interesting. Remembering that for the three groups shown, the reference group to which they compare are households without children. Since all the three of them have a positive average partial effect, it means that we estimate the households with children to be more vulnerable to social exclusion. We either can see that we estimate that households with only one adult taking care of at least one child have a significantly increased probability (approximately more 24.9 p.p., which is definitely very high) of being socially excluded when compared to households without children, whilst households with children but at least two adults only have an increased probability of approximately 6 p.p. when compared to the reference group. On graphs XIII to XV Appendix II we can see the histograms of the partial effects and once again, we have many frequencies concentrating on absolute values, suggesting that the effect is stronger than the average suggests.

VI. Conclusion

In this dissertation we have analysed the profile of social exclusion for the Portuguese population. We defined as our goal to estimate the individual characteristics that contributes to a higher risk of experiencing social exclusion, and we were able to identify risk groups, and thus, to contribute to more knowledge about the social exclusion determinants. We are now in position to make some considerations.

The social exclusion indicator we adopted stands with the Eurostat criteria, considering as socially excluded anyone who is living in a household with very low work intensity, experiencing material deprivation, or at risk of poverty. As expected, factors as education, marital status, health and household composition revealed to be very important. We can state that education plays a major role in society to struggle social exclusion and thus, it cannot be forgotten as a key factor to take in consideration when thinking of public policies aiming to bring down social exclusion among population. The significance related to employed female also suggests that women still have to struggle more than men to reach the same life standards. People living in scarcely populated areas also showed to be more vulnerable. We can think of this in two ways. First, people with lower life expectations are pushed away from urban centres; and second, the public services are not so accessible for them, as well as a higher distance from higher dense work stations areas can keep them from accepting or looking for better opportunities. Another expected result is the one relative to the unemployed. Few things can be said here. It is reasonable to think that unemployed people are more likely to face risk of poverty, to live in households with very low work intensity, and more likely to be less educated. So this can lead to a more severe state of social exclusion. A further investigation on this would be interesting to see how each of these determinants contributes, not only to experience social exclusion, but to experience a more severe state of social exclusion. Perhaps the most clearly vulnerable groups detected, are the children. The households with children are more likely to be socially excluded than households without children. This may require a special attention, as according to Hobcraft and Kiernan (1999), child poverty (and hence, social exclusion) increases the probability of early motherhood, which in turn increases the probability of experiencing social exclusion in adult life. Among the households with children, the most vulnerable were the households with only one adult (the probability of being socially excluded is much higher than the households with at least two adults), and it is expectable that this strongly relates to lone parenthood, which is supported by the results presented by Poggi (2007), Tsakloglou and Papadopoulos (2002) and Bradshaw *et al.* (2000).

Although, this work presents some limitations. The major one relates to the selection problem we faced. Excluding people that did not completed the inquiry is likely to exclude vulnerable individuals, since we proved these people to be in average less educated and older than the rest of the sample, so the results related to the elderly may not be consistent. A four years panel may also be short, especially if we think that through these years Portugal was strongly affected by an economic recession, and it seems reasonable to ask how much this impact the social exclusion determinants. Therefore, it would be interesting to see the results for a longer panel and to see how much would the social exclusions' determinants change in a full employment economic scenario. Another interesting idea, would be to investigate how much each determinant contribute not just for social exclusion, but for different degrees of social exclusion severity. This would be easily done using the same social exclusion criteria we used, but counting for in how many dimensions (among the three used by Eurostat) is the person socially excluded, instead of a binary indicator.

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Appendix 1 – Tables

	Random Effects Probit			**Pooled Probit**			**Pooled Probit (final model)**		
	Coefficient	σ	p-value	Coefficient	σ	p-value	Coefficient	σ	p-value
sol	0.105	0.183	0.566	0.012	0.118	0.921	-0.384	0.058	0.000
cas	-0.618	0.160	0.000	-0.405	0.109	0.000	-	-	-
viuv	-0.184	0.205	0.371	-0.142	0.135	0.294	-	-	-
ter	-1.416	0.150	0.000	-0.886	0.099	0.000	-0.873	0.098	0.000
sec	-0.557	0.104	0.000	-0.445	0.067	0.000	-0.437	0.067	0.000
saude	-0.219	0.065	0.001	-0.141	0.050	0.005	-0.152	0.050	0.002
ssaude	0.258	0.075	0.001	0.357	0.059	0.000	0.368	0.058	0.000
moradia	0.126	0.083	0.128	0.086	0.053	0.105	0.072	0.051	0.161
prop	-0.896	0.113	0.000	-0.629	0.070	0.000	-0.627	0.063	0.000
rendinf	0.076	0.146	0.601	-0.026	0.104	0.805	-	-	-
alojgrat	-0.283	0.165	0.085	-0.269	0.108	0.012	-0.266	0.104	0.011
den_p	0.130	0.074	0.078	0.057	0.053	0.283	-	-	-
frac_p	0.141	0.074	0.057	0.113	0.051	0.028	0.088	0.049	0.071
fem	0.125	0.100	0.212	0.066	0.066	0.316	-	-	-
fememp	-0.266	0.129	0.040	-0.190	0.089	0.033	-0.180	0.059	0.002
emp	-0.034	0.112	0.758	-0.071	0.080	0.377	-	-	-
desemp	0.398	0.115	0.001	0.212	0.082	0.010	0.261	0.073	0.000
idade	0.047	0.016	0.002	0.027	0.010	0.006	0.023	0.009	0.010
$idade^2$	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.002
dmasc	-0.026	0.160	0.870	-0.053	0.107	0.617	-	-	-
uaumc	1.030	0.337	0.002	0.702	0.230	0.002	0.761	0.199	0.000
daudc	0.539	0.217	0.013	0.180	0.151	0.233	0.207	0.073	0.004
datcoo	0.604	0.212	0.004	0.175	0.144	0.226	0.204	0.065	0.002
cd	-0.250	0.126	0.047	-0.004	0.091	0.964	-	-	-
desempbar	1.351	0.199	0.000	0.765	0.123	0.000	0.779	0.123	0.000
Log-Likelihood	-3520.9097			-4116.4164			-4122.5356		

Table I – Comparison between both random effects probit and pooled probit initial models, and final model pooled probit

	Random Effects Probit			Pooled Probit		
	dy/dx	σ	p-value	dy/dx	σ	p-value
sol	0.022	0.039	0.574	0.003	0.034	0.921
cas	-0.136	0.038	0.000	-0.122	0.034	0.000
viuv	-0.035	0.037	0.344	-0.040	0.036	0.276
ter	-0.183	0.013	0.000	-0.206	0.017	0.000
sec	-0.099	0.016	0.000	-0.118	0.016	0.000
saude	-0.044	0.013	0.001	-0.041	0.014	0.005
ssaude	0.055	0.017	0.001	0.109	0.019	0.000
moradia	0.025	0.016	0.121	0.025	0.015	0.101
prop	-0.222	0.032	0.000	-0.201	0.024	0.000
rendinf	0.016	0.031	0.610	-0.007	0.030	0.804
alojgrat	-0.052	0.028	0.058	-0.072	0.027	0.007
den_p	0.027	0.015	0.083	0.016	0.015	0.285
frac_p	0.029	0.015	0.061	0.033	0.015	0.029
fem	0.025	0.020	0.212	0.019	0.019	0.315
fememp	-0.051	0.024	0.031	-0.054	0.025	0.029
emp	-0.007	0.023	0.758	-0.020	0.023	0.378
desemp	0.092	0.030	0.002	0.065	0.026	0.013
idade	0.000	0.001	0.592	-0.001	0.001	0.073
dmasc	-0.005	0.033	0.870	-0.015	0.031	0.619
uaumc	0.268	0.101	0.008	0.228	0.079	0.004
daudc	0.123	0.054	0.023	0.053	0.046	0.245
datcoo	0.139	0.054	0.010	0.052	0.044	0.238
cd	-0.049	0.024	0.041	-0.001	0.026	0.964
desempbar	0.273	0.038	0.000	0.221	0.035	0.000

Table II – Comparison between the estimated average partial effects of random effects probit and pooleed probit initial models

	dy/dx	σ	p-value
cas	-0.115	0.018	0.000
ter	-0.203	0.017	0.000
sec	-0.116	0.016	0.000
saude	-0.044	0.014	0.002
ssaude	0.113	0.019	0.000
moradia	0.021	0.015	0.157
prop	-0.201	0.021	0.000
alojgrat	-0.072	0.026	0.006
frac_p	0.026	0.014	0.073
fememp	-0.051	0.016	0.002
desemp	0.080	0.024	0.001
idade	-0.001	0.001	0.017
uaumc	0.249	0.068	0.000
daudc	0.062	0.022	0.006
datcoo	0.061	0.020	0.002
desempbar	0.225	0.035	0.000

Table III – Estimated average partial effects of the pooled probit final model

Descriptive Statistics											
Variable		Mean	σ	Min	Max	**Variable**		Mean	σ	Min	Max
sol	overall	0.227	0.419	0.000	1.000	**den_p**	overall	0.352	0.478	0.000	1.000
	between		0.412	0.000	1.000		between		0.435	0.000	1.000
	within		0.073	-0.523	0.977		within		0.198	-0.148	0.852
cas	overall	0.650	0.477	0.000	1.000	**frac_p**	overall	0.327	0.469	0.000	1.000
	between		0.466	0.000	1.000		between		0.424	0.000	1.000
	within		0.101	-0.100	1.400		within		0.201	-0.173	0.827
viuv	overall	0.069	0.254	0.000	1.000	**fem**	overall	0.519	0.500	0.000	1.000
	between		0.245	0.000	1.000		between		0.500	0.000	1.000
	within		0.066	-0.681	0.819		within		0.000	0.519	0.519
ter	overall	0.121	0.326	0.000	1.000	**emp**	overall	0.474	0.499	0.000	1.000
	between		0.318	0.000	1.000		between		0.458	0.000	1.000
	within		0.071	-0.629	0.871		within		0.198	-0.276	1.224
sec	overall	0.154	0.361	0.000	1.000	**desemp**	overall	0.096	0.294	0.000	1.000
	between		0.338	0.000	1.000		between		0.233	0.000	1.000
	within		0.128	-0.596	0.904		within		0.181	-0.654	0.846
saude	overall	0.457	0.498	0.000	1.000	**idade**	overall	50.281	17.023	16.000	80.000
	between		0.415	0.000	1.000		between		16.990	17.500	80.000
	within		0.276	-0.293	1.207		within		1.095	48.781	51.781
ssaude	overall	0.178	0.383	0.000	1.000	**dmasc**	overall	0.601	0.490	0.000	1.000
	between		0.314	0.000	1.000		between		0.467	0.000	1.000
	within		0.219	-0.572	0.928		within		0.147	-0.149	1.351
exc	overall	0.285	0.451	0.000	1.000	**uaumc**	overall	0.013	0.115	0.000	1.000
	between		0.359	0.000	1.000		between		0.102	0.000	1.000
	within		0.273	-0.465	1.035		within		0.051	-0.737	0.763
moradia	overall	0.657	0.475	0.000	1.000	**daudc**	overall	0.159	0.366	0.000	1.000
	between		0.460	0.000	1.000		between		0.337	0.000	1.000
	within		0.119	-0.093	1.407		within		0.142	-0.591	0.909
prop	overall	0.789	0.408	0.000	1.000	**datcoo**	overall	0.156	0.363	0.000	1.000
	between		0.395	0.000	1.000		between		0.329	0.000	1.000
	within		0.102	0.039	1.539		within		0.153	-0.594	0.906
rendinf	overall	0.045	0.206	0.000	1.000	**cd**	overall	0.395	0.489	0.000	1.000
	between		0.177	0.000	1.000		between		0.467	0.000	1.000
	within		0.106	-0.705	0.795		within		0.146	-0.355	1.145
alojgrat	overall	0.061	0.239	0.000	1.000	**fememp**	overall	0.238	0.426	0.000	1.000
	between		0.221	0.000	1.000		between		0.401	0.000	1.000
	within		0.092	-0.689	0.811		within		0.143	-0.512	0.988
						desempbar	overall	0.096	0.233	0.000	1.000
							between		0.233	0.000	1.000
							within		0.000	0.096	0.096

Table IV – Descriptive statistics of the variables considered

Description of the variables			
sol	Equal to 1 if single, 0 otherwise	**frac_p**	Equal to 1 if lives in a scarcely populated area, 0 otherwise
cas	Equal to 1 if married, 0 otherwise	**fem**	Equal to 1 if female, 0 otherwise
viuv	Equal to 1 if widow or widower, 0 otherwise	**fememp**	Equal to 1 if female and employed, 0 otherwise
ter	Equal to 1 if have tertiary education, 0 otherwise	**emp**	Equal to 1 if employed, 0 otherwise
sec	Equal to 1 if have secondary education, 0 otherwise	**desemp**	Equl to 1 if unemployed, 0 otherwise
saude	Equal to 1 if have good or very good health, 0 otherwise	**idade**	age
ssaude	Equal to 1 if have bad or very bad health, 0 otherwise	**dmasc**	Equal to 1 if lives in a household with two or more adults without children, 0 otherwise
moradia	Equal to 1 if lives in a detached house, 0 otherwise	**uaumc**	Equal to 1 if lives in a household with one adult anda t least one child, 0 oterwise
prop	Equal to 1 if owns the accommodation, 0 otherwise	**daudc**	Equal to 1 if lives in household with two adults and one or two children, 0 otherwise
rendinf	Equal to 1 if if lives in a rented house with a supported rent, 0 otherwise	**datcoo**	Equal to 1 if lives in a household with two adults and three or more children or more than two adults with at least one child, 0 otherwise
alojgrat	Equal to 1 if lives in an accommodation provided by someone else without any costs or provided by in exchange for a wage, 0 otherwise	**cd**	Equal to 1 if lives in a household with dependent children, 0 otherwise
den_p	Equal to 1 if lives in a highly populated area, 0 otherwise		

Table V – Meaning of the variables

	Exc
2010	27.66%
2011	27.36%
2012	28.81%
2013	30.00%

Table VI – Frequency of social exclusion in the sample at each year

	All	LWI and Pov	LWI and Depr	Depr and Pov	LWI	Depr	Pov	Total
2010	4.32%	1.80%	2.34%	12.41%	4.50%	44.24%	30.40%	100.00%
2011	4.55%	2.18%	1.64%	12.18%	6.18%	44.36%	28.91%	100.00%
2012	7.94%	1.90%	1.55%	10.19%	8.29%	43.52%	26.60%	100.00%
2013	6.80%	2.82%	3.81%	12.27%	6.14%	47.10%	21.06%	100.00%

Table VII – Proportion of each possible combination of social exclusion dimensions among the socially excluded in the sample

	LWI	Pov	Depr
2010	3.58%	13.53%	17.51%
2011	3.98%	13.08%	17.16%
2012	5.67%	13.43%	18.21%
2013	5.87%	12.89%	21.00%

Table VIII – Proportion of each social exclusion dimension in the sample

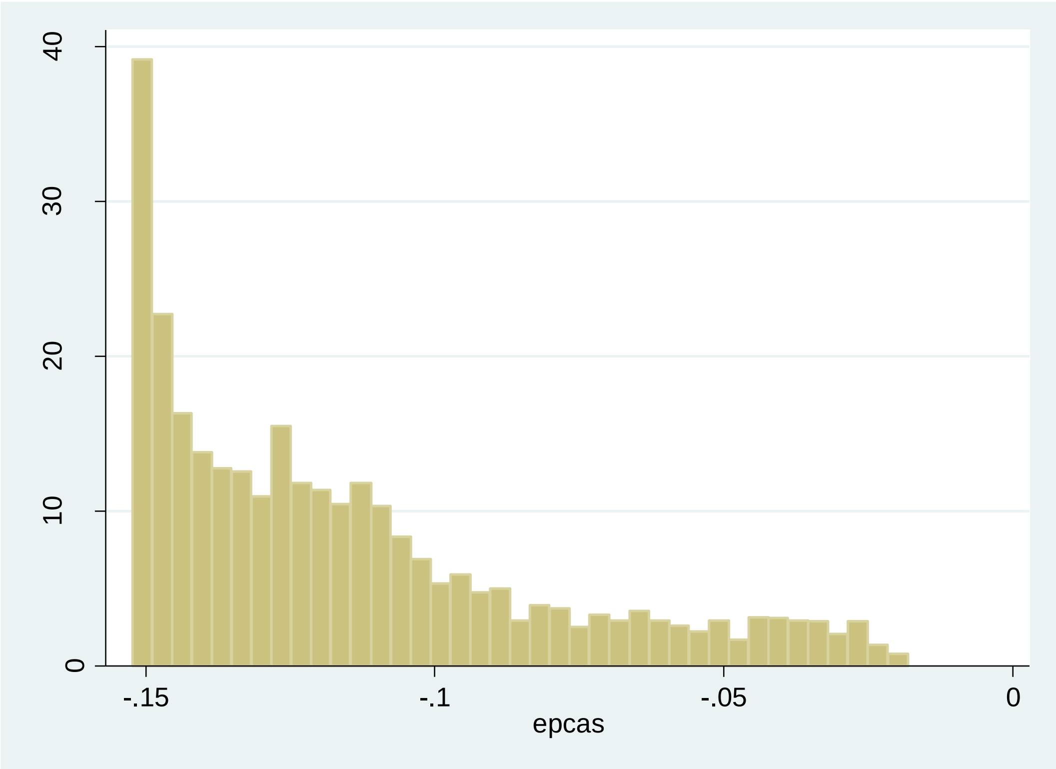
	Income Median
2010	7575.956522
2011	7644
2012	7489.813658
2013	7362.580645

Table IX – Income median by adult equivalent in each year

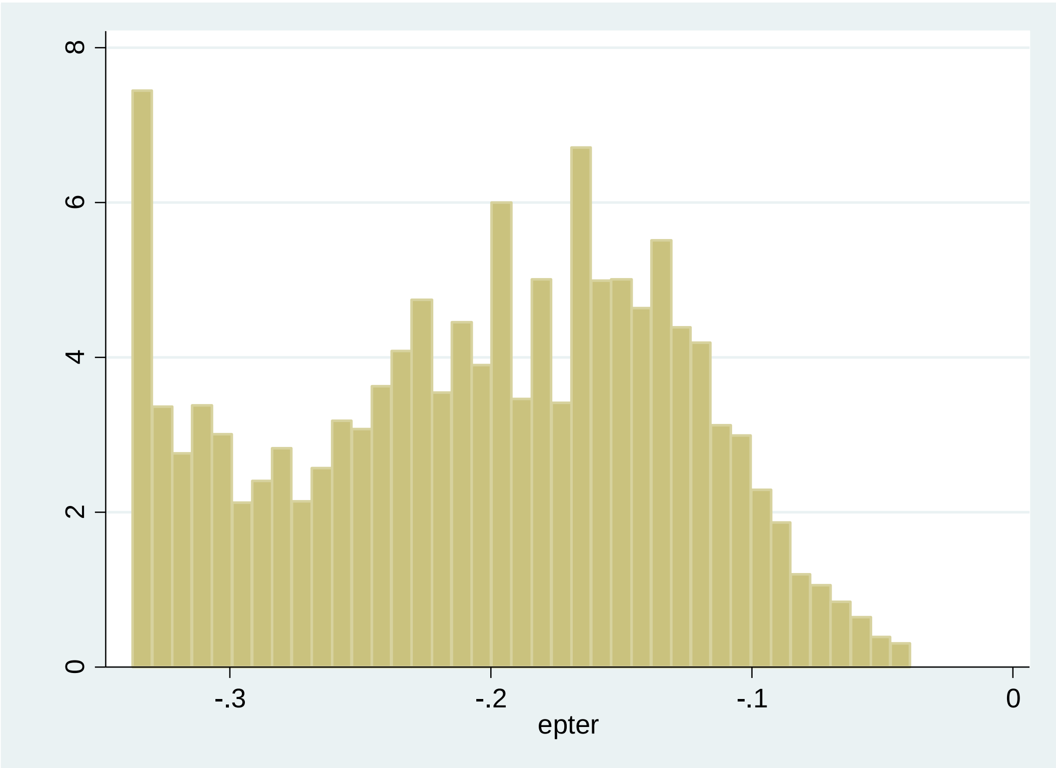
Likelihood-ratio test			
Assumptions: $\beta_{sol} = \beta_{viuv} = \beta_{den\_p} = \beta_{fem} = \beta_{emp} = \beta_{dmasc} = \beta_{cd} = \beta_{rendinf} = 0$ plus:			
None	$\beta_{moradia} = 0$	$\beta_{frac\_p} = 0$	$\beta_{moradia} = \beta_{frac\_p} = 0$
LR $chi^2_{(8)} = 12.24$ p-value = 0.141	LR $chi^2_{(9)} = 15.81$ p-value = 0.071	LR $chi^2_{(9)} = 18.25$ p-value = 0.032	LR $chi^2_{(10)} = 25.59$ p-value = 0.004

Table X - comparison of different likelihood-ratio tests testing for different restrictions on the model

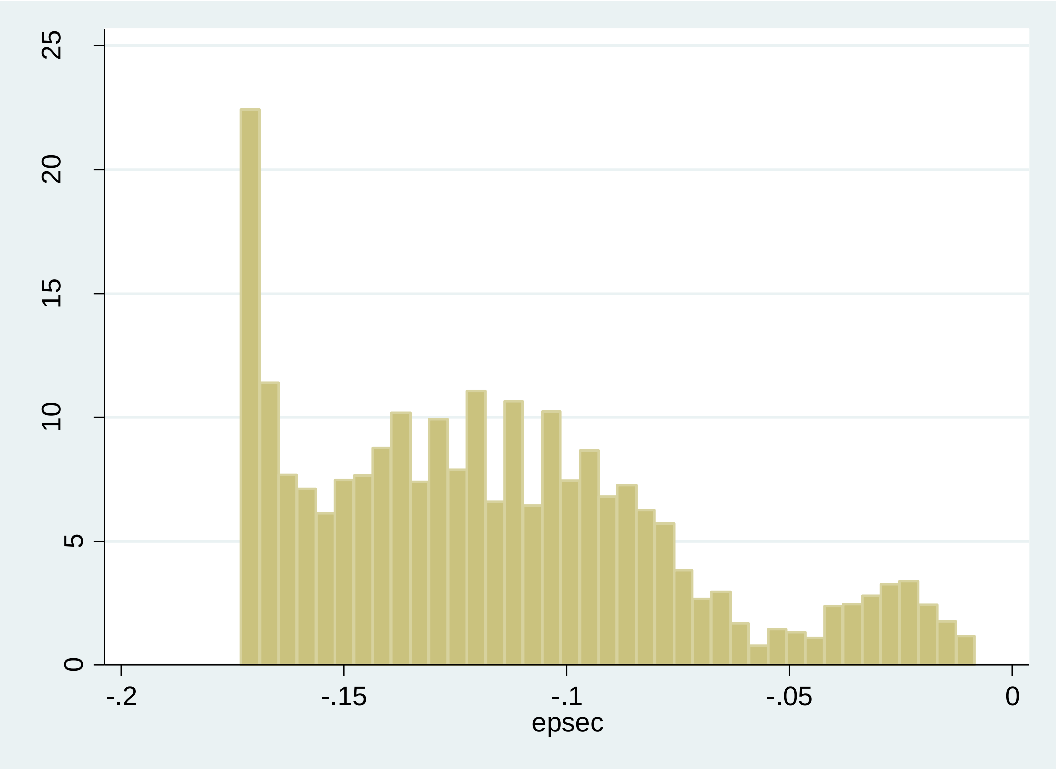
Appendix 2 - Graphs



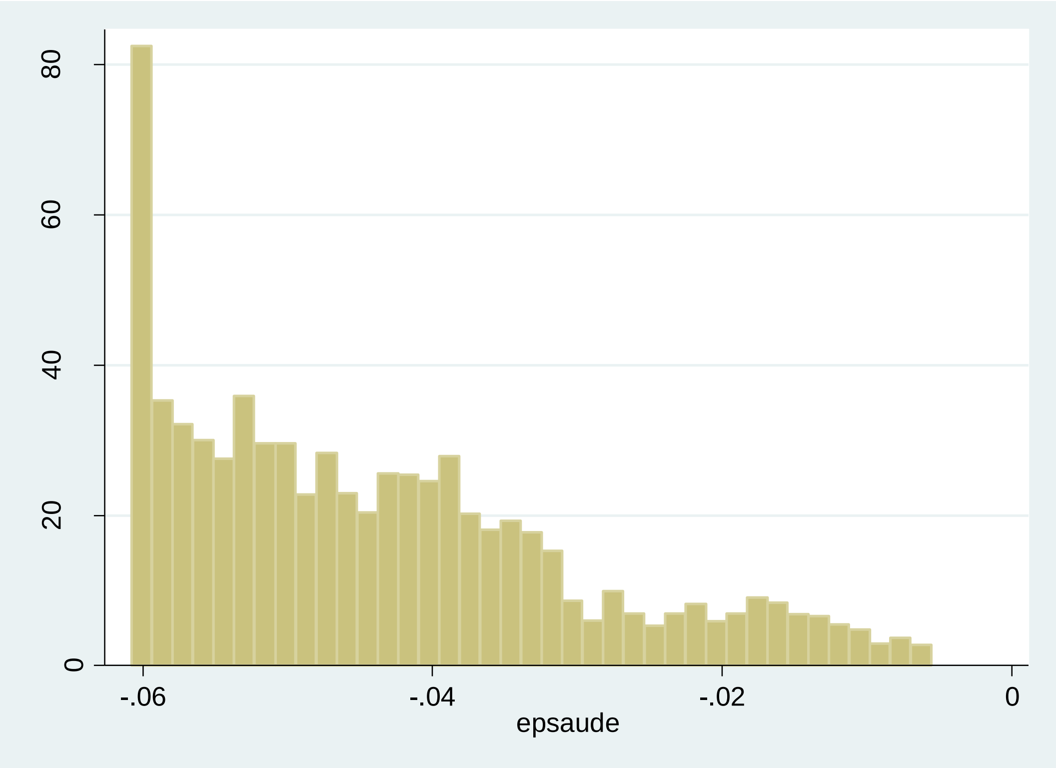
Graph I– Histogram of partial effects of married



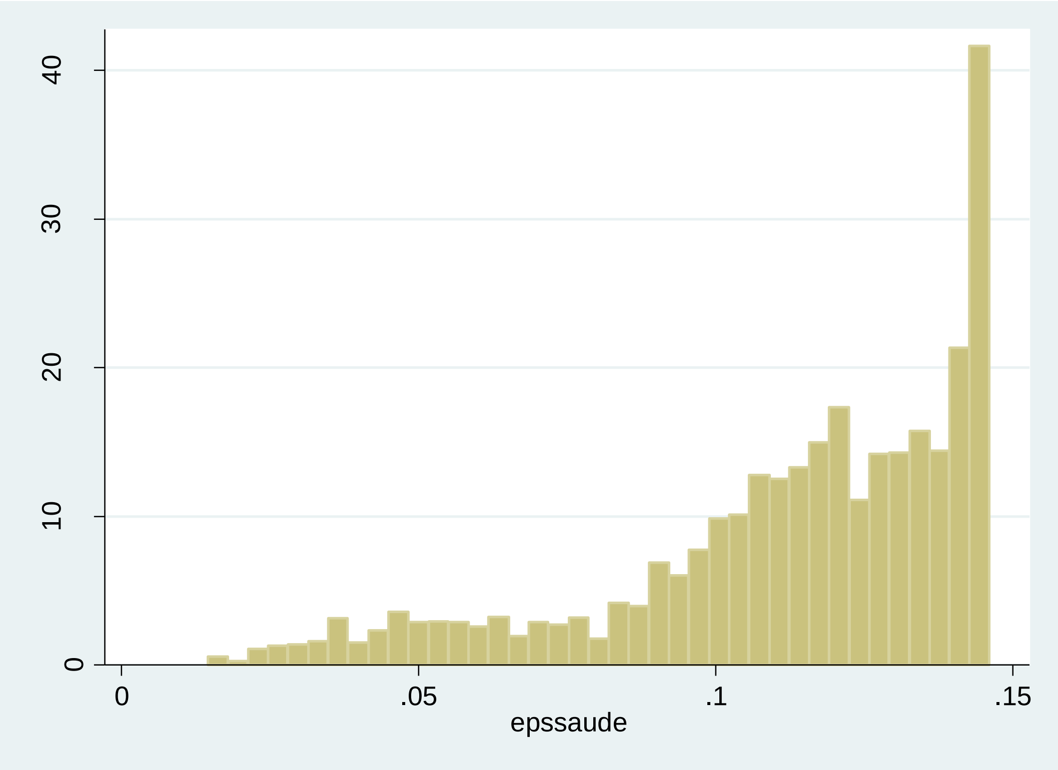
Graph II – Histogram of partial effects of tertiary education



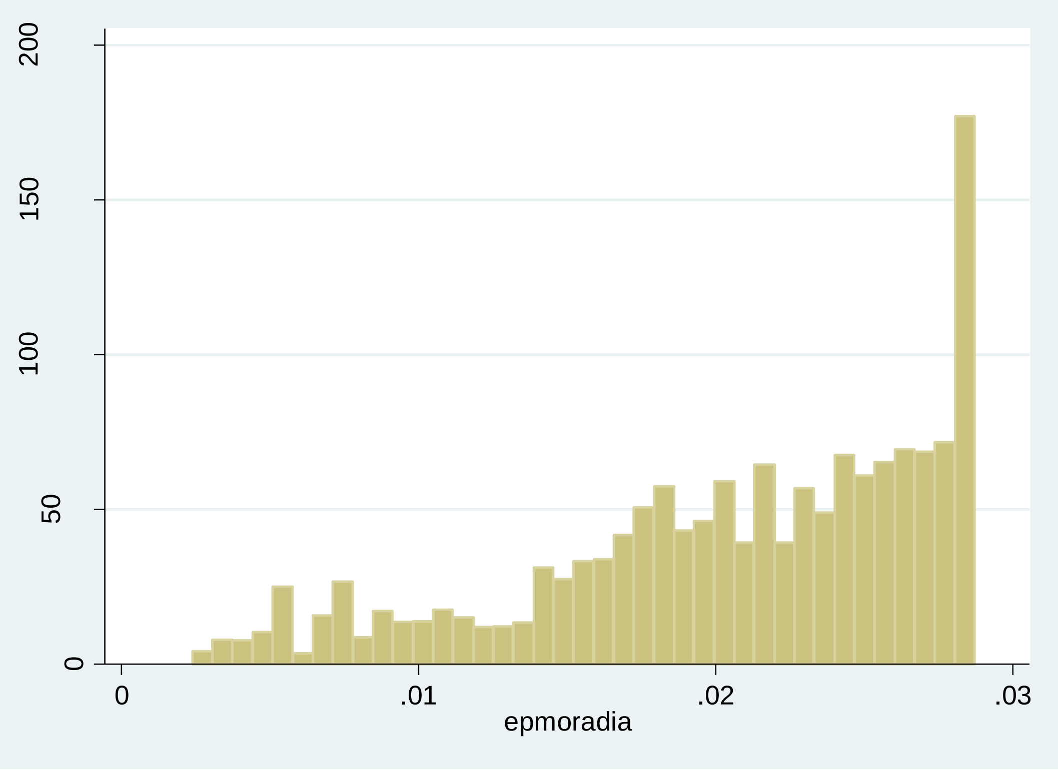
Graph III – Histogram of partial effects of secondary education



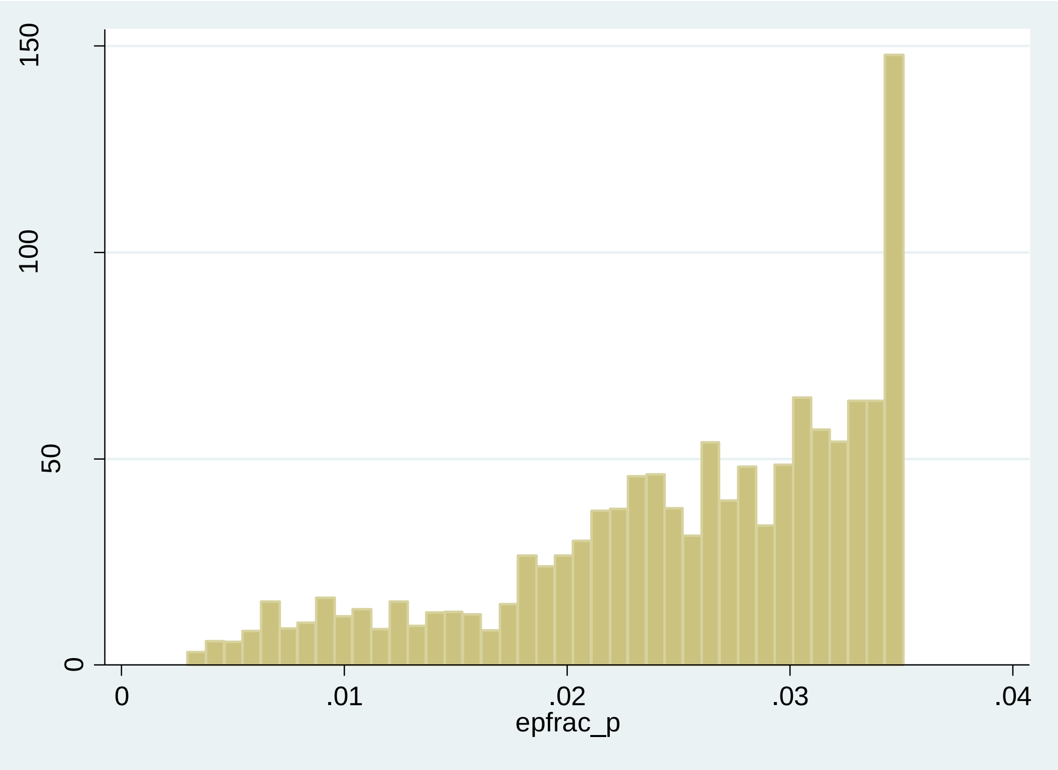
Graph IV – Histogram of partial effects of good and very good health status



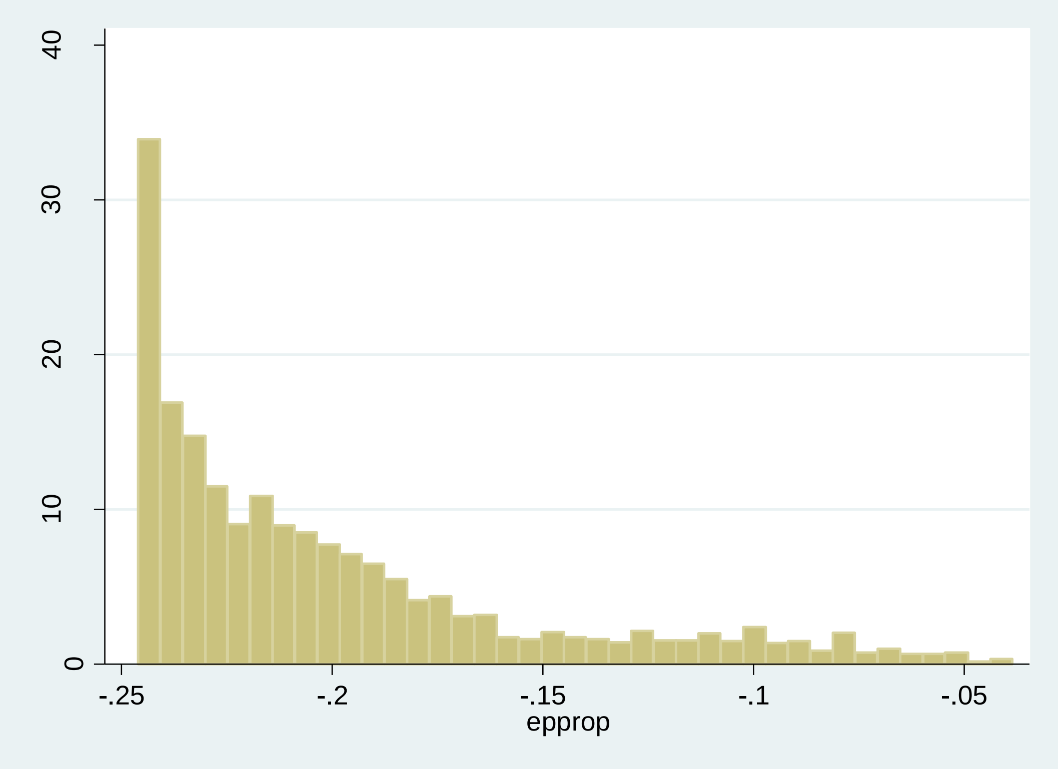
Graph V – Histogram of partial effects of bad and very bad health status



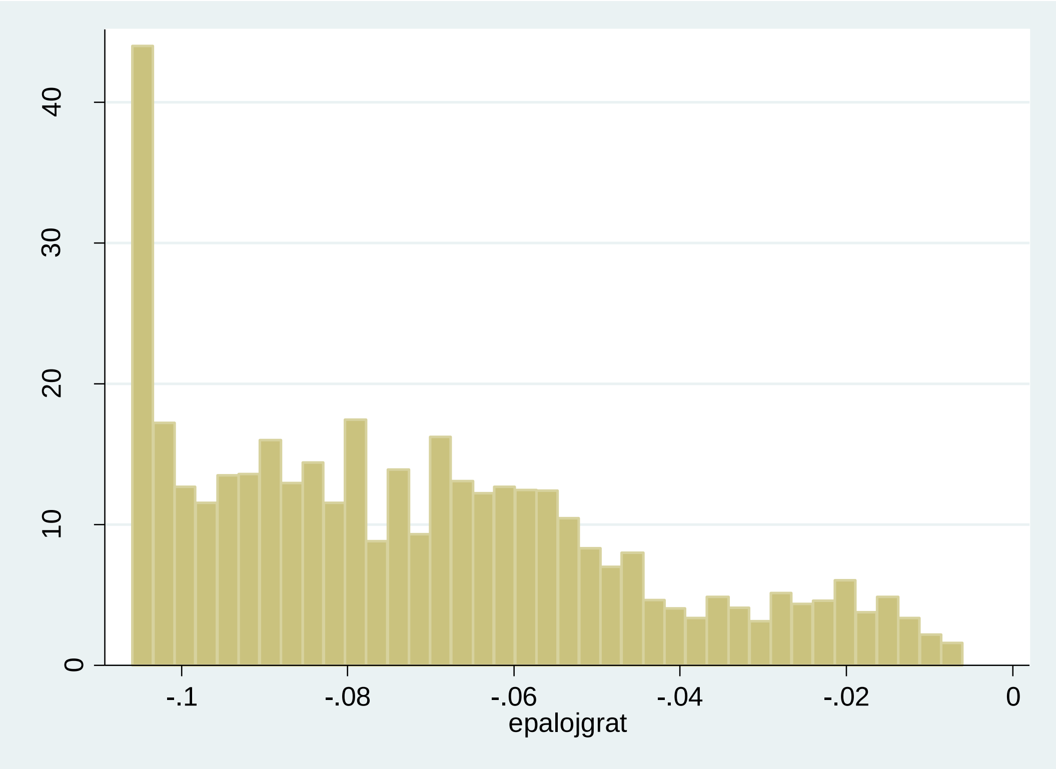
Graph VI – Histogram of partial effects of living in a house



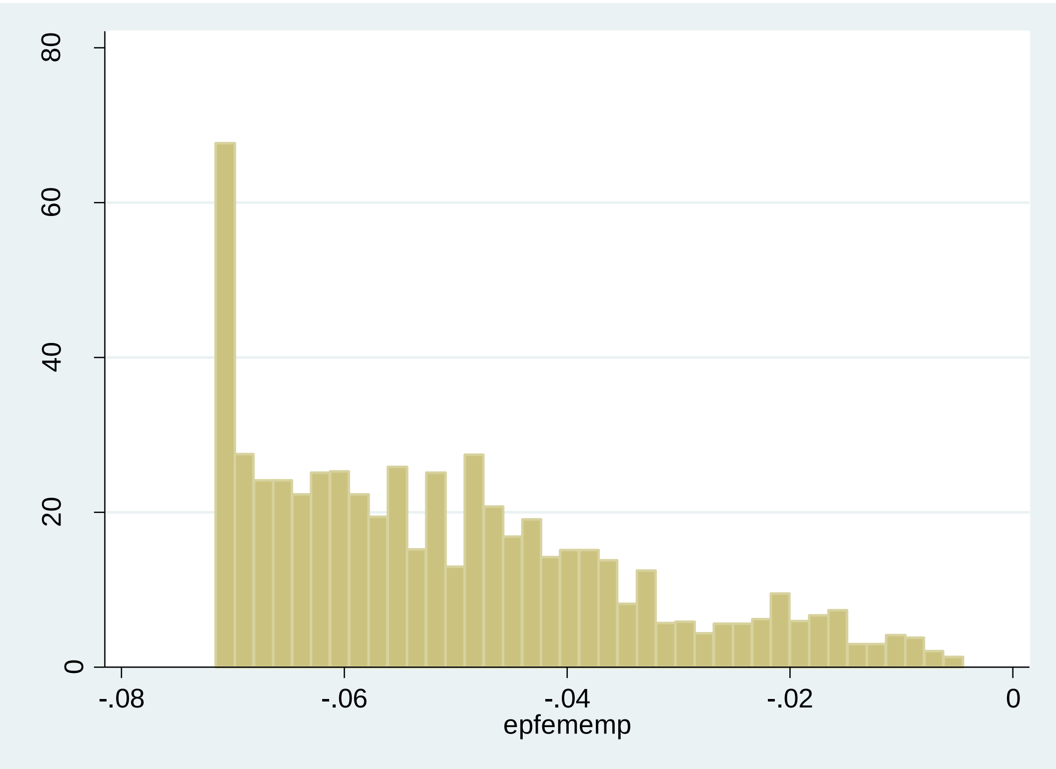
Graph VII – Histogram of partial effects of living in a scarcely populated area



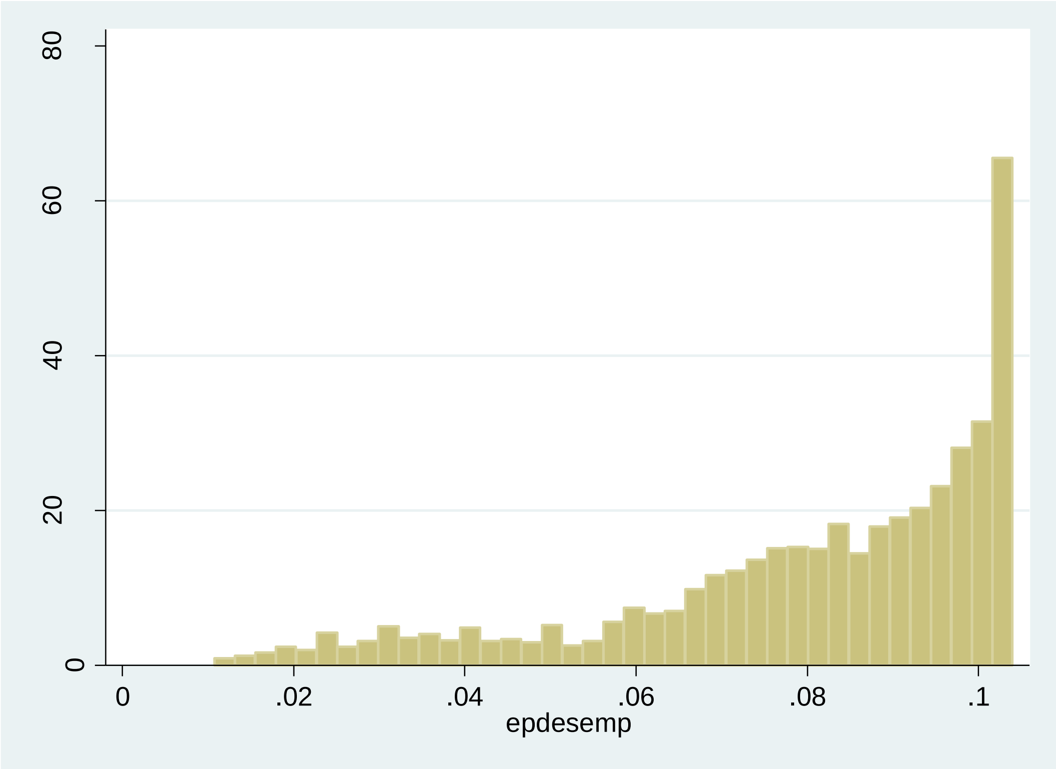
Graph VIII – Histogram of partial effects of being the owner of the accommodation



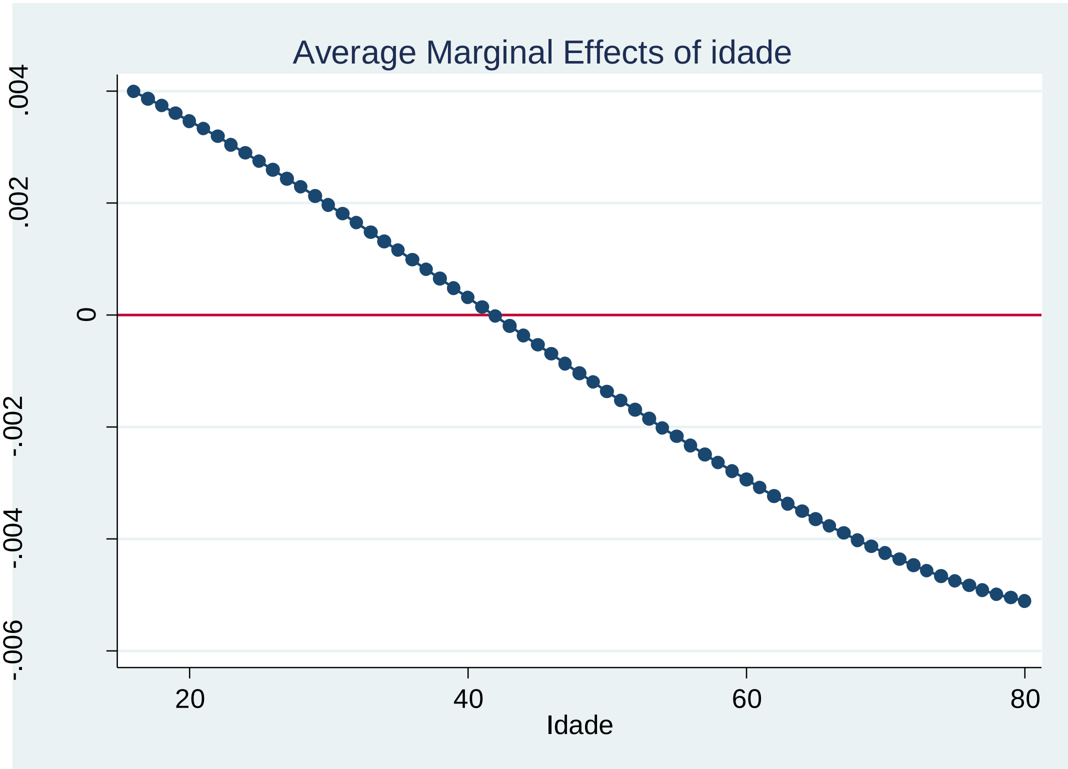
Graph IX – Histogram of partial effects of living in an accommodation provided by someone else without any costs or provided by in exchange for a wage



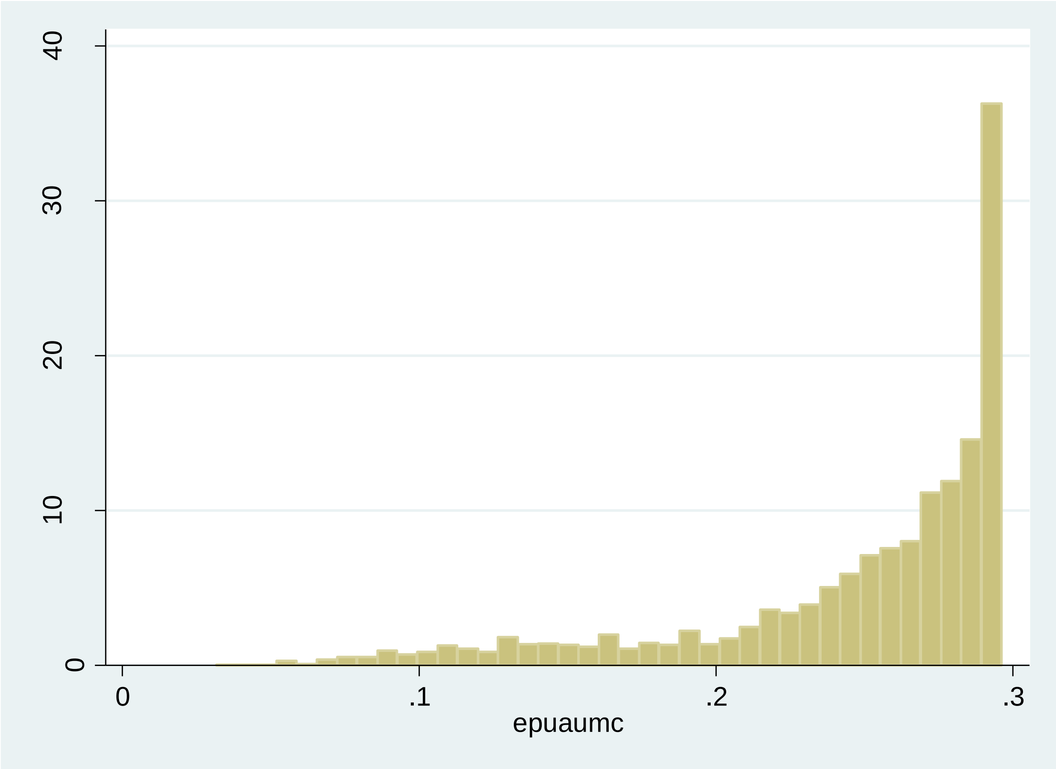
Graph X – Histogram of partial effects of being an employed female



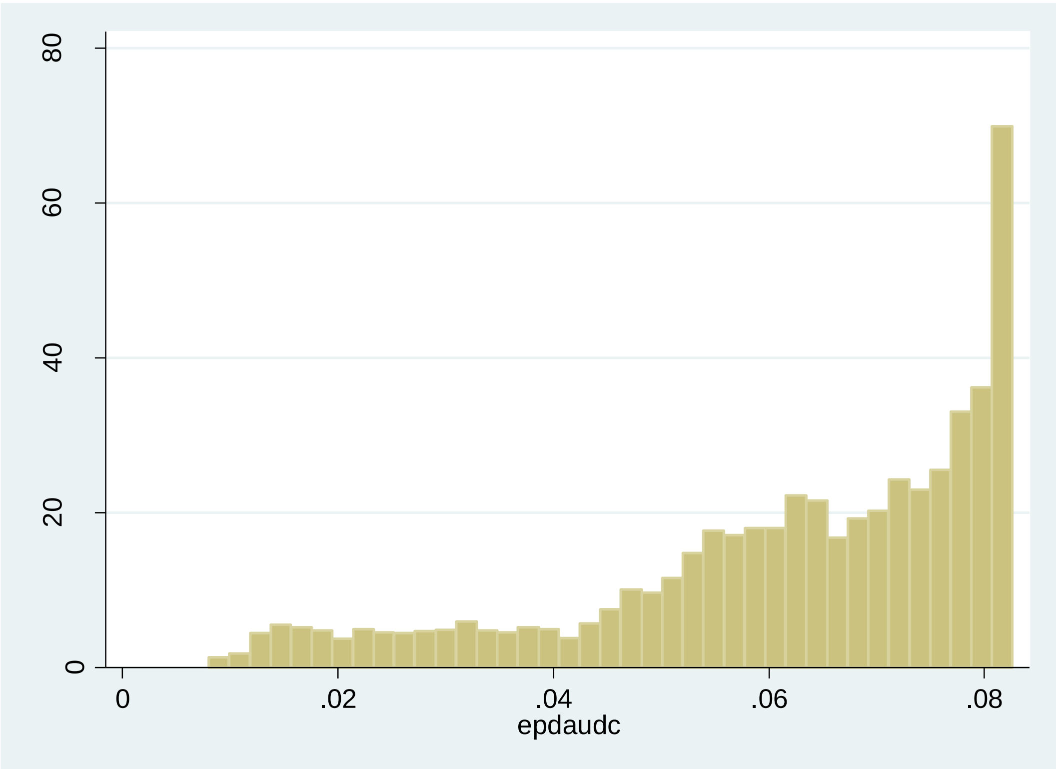
Graph XI – Histogram of partial effects of being unemployed



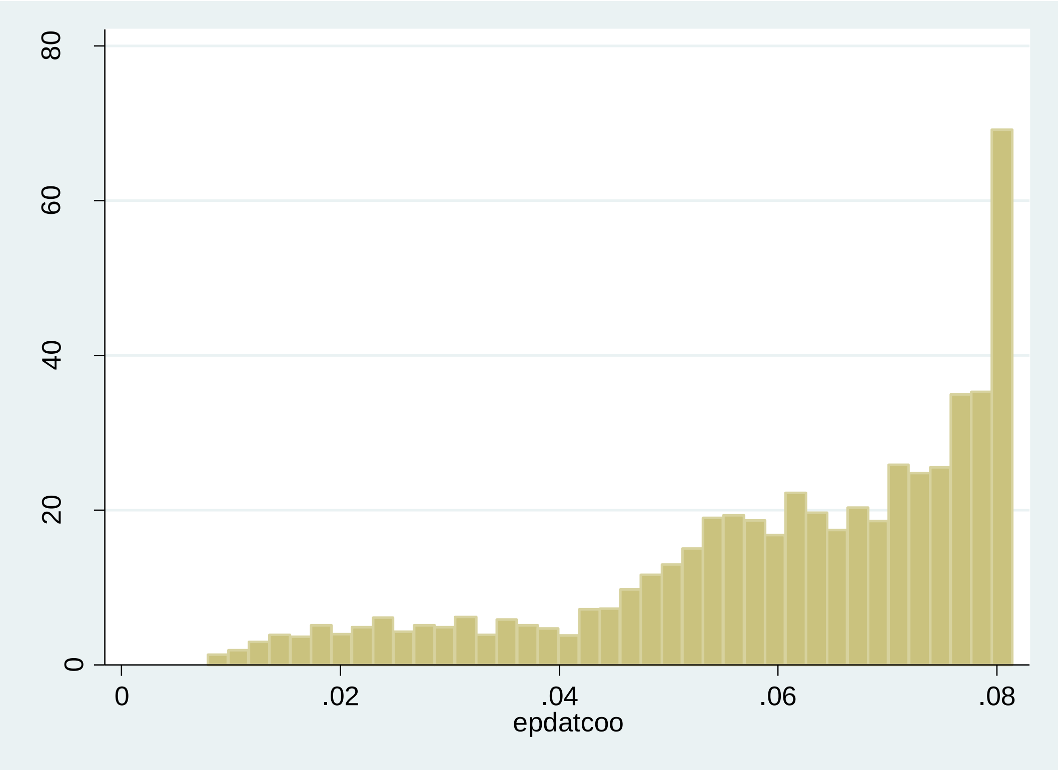
Graph XII – Average partial effects across age



Graph XIII – Histogram of partial effects of households with one adult and at least one child



Graph XIV – Histogram of partial effects of households with two adults and one or two children



Graph XV – Histogram of households with two adults and at least three children or more than two adults with at least one child