Departament d'Economia Aplicada

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María Cervini Pla

DOCUMENT DE TREBALL

09.04

Universitat Autònoma de Barcelona
Facultat de Ciències Econòmiques i Empresarials

Aquest document pertany al Departament d'Economia Aplicada.

Data de publicació : **Maig 2009**

Departament d'Economia Aplicada
Edifici B
Campus de Bellaterra
08193 Bellaterra

Telèfon: (93) 581 1680
Fax:(93) 581 2292
E-mail: d.econ.aplicada@uab.es
http://www.ecap.uab.es

Measuring intergenerational earnings mobility in Spain: A selection-bias-free approach*

María Cervini Plá †

May 13, 2009

Abstract

This paper analyses intergenerational earnings mobility in Spain correcting for different selection biases. We address the co-residence selection problem by combining information from two samples and using the two-sample two-stage least square estimator. We find a small decrease in elasticity when we move to younger cohorts. Furthermore, we find a higher correlation in the case of daughters than in the case of sons; however, when we consider the employment selection in the case of daughters, by adopting a Heckman-type correction method, the difference between sons and daughters disappears. By decomposing the sources of earnings elasticity across generations, we find that the correlation between child's and father's occupation is the most important component. Finally, quantile regressions estimates show that the influence of the father's earnings is greater when we move to the lower tail of the offspring's earnings distribution, especially in the case of daughters' earnings.

Keywords: Intergenerational mobility, earnings, two sample two stage least square estimator, Spain.

JEL classification: D31, J31, J62.

*I would like to thank Xavier Ramos, Olga Cantó and Cheti Nicoletti for their useful suggestions. I am also grateful to participants at XXXIII Simposio Análisis Económico in Zaragoza and XVI Encuentro de Economía Pública in Granada for helpful comments on a previous version of this paper. This research was initiated while I was visiting the Institute for Social and Economic Research (University of Essex) with an ECASS Scholarship. Financial support from projects SEJ2004-07373-C03-01/ECON and SEJ2007-67911-C03-02/ECON (Ministerio de Ciencia y Tecnología) is gratefully acknowledged.

†Departament d'Economia Aplicada. Universitat Autònoma de Barcelona. Edificio B, 08193 Bellaterra (Barcelona), Spain. Phone number +3493 581 4575/Fax +3493 581 2292. E-mail: maria.cervini@uab.es

1 Introduction

Intergenerational mobility refers to the association between socio-economic achievements of parents and those of their children. If we believe that equal opportunity is a desirable characteristic of society, a high degree of intergenerational mobility is an important indicator of the healthiness and success of society. In this context, children from different families are not predetermined by their parents and have equal options to achieve education and higher earnings (Behrman and Taubman (1990)).

Intergenerational mobility studies usually estimate the correlation between socio-economic status of parents and their offsprings. On one hand, a high correlation would imply that people born in disadvantaged families have a smaller chance to occupy the highest socio-economic positions than those born in privileged families. On the other hand, a zero correlation would imply a high degree of mobility and more equal opportunities. Economists have primarily concentrated on the relationship between parents and their offsprings' permanent incomes or earnings, while sociologists explore the association measures between ordered categorical variables, such as social and economic class position.[1]

In this paper, we follow the economic approach and focus on intergenerational mobility measured by the intergenerational elasticity of offsprings' earnings with respect to their fathers' earnings. However, the estimation of intergenerational mobility can be bias due to different sample selection problems. Therefore, the main objective of this paper is to study intergenerational earnings mobility in Spain and attempt to correct the associated main sample selection problems.

Why Spain? The literature on intergenerational earnings mobility has been concentrated in the United States, Canada, and some European countries, including England, Scandinavian countries, Germany, and France. However, there is comparably less evidence for the intergenerational mobility in southern European countries, probably due to the lack of long panels. As far as we know, the only exception is the study of Mocetti (2007) wherein he explores intergenerational earnings mobility in Italy.

As in other southern European countries, Spain experiences stronger intergenerational family bonds compared to other countries. Indeed after leaving home, children

[1] See Solon (1999), Björklund and Jäntti (2000), Bowles and Gintis (2002), Erikson and Godthorpe (2002) for a review.

maintain a close relationship with parents. Therefore, it is valuable to explore how earnings mobility in Spain is compared to other countries, and it is particularly interesting to compare our results to those obtained by Mocetti (2007) for Italy.

Intergenerational mobility in Spain has primarily been studied by sociologists. For example, Carabaña (1999) studied occupational mobility. From an economic point of view, Hugalde (2004) is the only study for Spain that analyses intergenerational mobility. She analyses the intergenerational income and education mobility using the Family Expenditure Survey (Encuesta de Presupuestos Familiares) for 1980 and 1990; however, she only estimates the elasticity when children and their fathers live together.

As previously mentioned, we try to correct the main selection problems. One of these problems arise from the fact that, in a panel, we have information regarding offsprings' and parents' earnings when they live together in at least one wave; however, the probability of observing offspring living with their parents decreases as the children grow older. Thus, in short panels, it is impossible to follow children during their adult life. This generates a bias in the estimation of intergenerational correlation. Following Nicoletti and Francesconi (2006) we can refer to this sample selection problem as **co-residence selection.**[2] This selection problem is particularly important in Spain, where we have only short panels, and thus, do not have information on both children's and their fathers' permanent earnings. When we have information regarding the father, the children are too young to observe their permanent earnings, and when we have adults, we do not have information about their father's earnings.

In order to overcome this selection problem, it is possible to consistently estimate intergenerational earnings mobility using the two-sample two-stage least square estimator.[3] This method combines information from two separate samples: a sample of adults (sons and daughters) with observations of their earnings and their parents' characteristics, and a sample of potential parents with observations on earnings and

[2] Nicoletti and Francesconi (2006) analyse intergenerational mobility using an occupational prestige score. They find that the β coefficient (in this case β represents the elasticity between father and offspring occupational prestige scores) is underestimated when they only consider the pairs of children and parent who are cohabiting.

[3] This method is asymptotically equivalent to the two-sample instrumental variable developed by Angrist and Krueger (1992), Arellano and Meghir (1992) and Ridder and Moffit (2006) and has been already applied to the study of intergenerational mobility by Björklund and Jäntti (1997) in Sweden; by Fortin and Lefebvre (1998) in Canada; by Grawe (2004)) in Ecuador, Nepal, Pakistan, and Peru; by Lefranc and Trannoy (2004) in France; by Nicoletti and Ermisch (2007) in Britain; and by Mocetti (2007) in Italy.

the same characteristics. The latter sample is used to estimate an earnings equation for parents using their characteristics as explanatory variables, while the former is used to estimate an intergenerational earnings equation by replacing the missing parents' earnings with its best linear prediction.

The second problem we try to correct is the **employment selection**, wherein we only have earnings for adults who are employed. Since the decision to work or not work is not random, especially in the case of women, estimating intergenerational earnings mobility only for those who are working gives us biased estimators. We deal with this selection problem, in the case of daughters, by using the Heckman-type of correction estimation described in Vella (1998) and used in Ermisch, Francesconi, and Siedler (2006).

Thus, the main contribution of this paper is the analyze of intergenerational earnings mobility in Spain for all adults, that is, those who live and those who do not live with their parents. Another important contribution of our paper is the consideration of employment selection. As a result, we take into account the two major selection problems of the short panel. Furthermore, we investigate more of the characteristics of this earnings transmission through two exercise. First, we do a decomposition of the sources of earnings elasticity, and second, we investigate the influence of fathers' earnings by quantiles.

When we correct for the co-residence selection problem, we find an elasticity of 0.38 for sons between 30 and 40 years old and an elasticity of 0.42 for sons between 40 and 50 years old. In the case of daughters, we obtain elasticities of 0.50 and 0.58 respectively. We thus find a slightly lower elasticity when we move to younger cohorts. Furthermore, we obtain lager elasticities for daughters; however, when we consider the employment selection in regard to women, the differences disappear. By decomposing the sources of earnings correlations, we find that the correlation between children's and father's occupation is the most important component. A father's occupation is a good indicator of his social position and is better than his education as a predictor of his children's earnings.

Finally, we estimate the elasticity between children's and fathers' earnings by quantiles. We find that the influence of the fathers' earnings is greater when we move to the lower tail of the distribution, especially in the case of daughters. By comparing the elasticities obtained in Spain with the results for other countries, we find that intergenerational mobility in Spain is similar to mobility in France, is lower than in Nordic countries and Britain, and is higher than in Italy and the United States.

The rest of the paper is organised as follows. In the next section, we present a very simple theoretical framework that allows us to understand some of the sources of earnings transmission between generations. Section 3 describes how we implement the two-sample two-stage least square estimator. In Section 4 we describe the data source, the selection sample, and the variables used in the empirical analysis. Section 5 reports the results, and finally, Section 6, concludes with some final remarks.

2 Sources of earnings transmission

Why do some children obtain better jobs and higher earnings when they become adults, while others do not? Which are the channels through which earnings are transmitted?

As Nicoletti and Ermisch (2007) point out, an important number of institutions affect intergenerational mobility, like the educational system, the labour market, the family (particularly its investment in children). Furthermore, public policy affects these institutions and hence the intergenerational mobility.

Following Checchi (2006) and Lefranc and Trannoy (2004), we present here a simple model that allows us to better understand some of the sources of intergenerational earnings transmission.[4]

Let us suppose an individual belonging to family i and to generation t, whose permanent earnings W_{it} derives from two components: ability endowment A_{it}, and human capital (i.e., education E_{it}). If we do not consider on-the-job training, education is previous to get into the labour market, and is therefore, with respect to earnings. If we consider the fact that ability increases labour productivity, we can express these channels as follows:

$$W_{it} = \lambda E_{it} + \pi A_{it} + \mu_{it} \tag{1}$$

Where the relationship between earnings, education and ability is assumed to be linear for simplicity, and μ_{it} is an independent and identically distributed (i.i.d.) error

[4]Here we will summarise the main channels of earnings transmission; however, most of these channels are the same when we analyse the transmission of income.

term that captures the idea of luck in the labour market.

Education is one of the most important channels of intergenerational earnings transmission. We represent the education of previous generation by E_{it-1}. Education attainment can be determined by the cultural influence of the family (described by η). There is a large body of empirical evidence about how children of educated parents are more likely to acquire education. As Checchi (2006) points out, this may be partly due to parent imitation, but in most cases, it works through induced educational choices. An educated parent is better aware of the psychological and economic value of education, and therefore, puts more pressure on his or her children to achieve more at school.

Furthermore, in the presence of liquidity constraints, education is also determined by family earnings, reducing the optimal investment into education by poor families. We indicate this channel with the γ and we write:

$$E_{it} = \eta E_{it-1} + \gamma W_{it-1} \tag{2}$$

Therefore, education is determined by the education and earnings of the previous generation; however, if we substitute E_{it-1} with the expression with one-period lag successively we can observe that education depends on the earnings of the parents, grandparents, and previous generations.

The second component we have in equation 1 is ability. Considering that ability is genetically (or mechanically) inherited, we can indicate this effect with α, while $t-1$ represents again the previous generation. Ability can influence earnings directly through the type of job obtained because people with greater ability are more productive. Therefore, we have:

$$A_{it} = \alpha A_{it-1} \tag{3}$$

This component can be thought of as some aspects of earnings determinants that "money can't buy", and at the same time, are transmitted from one generation to the next. Examples of this are the transmission of intelligence quotient (IQ), social network, and preferences.

Another source of intergenerational earnings persistence emerges from territorial segregation. One's neighbourhood can influence earnings through education (better quality of schools) or through social capital (good neighbours allow to obtain better jobs). Neighbourhoods with better schools and better neighbours generally have higher house prices. Therefore, at the end, residential choices are determined by family earnings.

Another channel is networks *per se*. Obtaining a good and well-paid job may depend on friends and social networks rather than on one's curriculum.

We consider the combined effect of family networking and residential choices on offspring's earnings. Since both components are related to family earnings, we indicate this channel with the θ and extend equation 1 with an additional term:

$$W_{it} = \lambda E_{it} + \pi A_{it} + \theta W_{it-1} + \mu_{it} \tag{4}$$

Taking into account each of these channels, we can observe that intergenerational persistence is a dynamic system. From an empirical point of view, it is not easy to distinguish between alternative explanations of intergenerational persistence of earnings. It is important to note, that in a simple regression of child's earnings on parents' earnings, the coefficient will simultaneously capture all of the effects "that money can buy". Hence, standard estimates of intergenerational earnings regressions will provide an upward-biased estimates of the causal effect of fathers' earnings on their children's earnings. Concretely, we will estimate:

$$W_{it} = \beta W_{it-1} + \mu_{it} \tag{5}$$

However, from a policy point of view, the distinction between the different components matters to the prediction of the impact of economic policies or to the knowledge of which policy could better improve mobility.

3 Estimation method

3.1 The econometric model

As we explained above, we focus on intergenerational mobility measured by the intergenerational elasticity of offsprings' earnings with respect to fathers' earnings. More precisely, we consider the following intergenerational mobility equation:

$$W_{it} = \alpha + \beta W_{it-1} + \mu_{it} \tag{6}$$

where W_{it} is the offspring's log earnings, W_{it-1} is the fathers' log earnings (the earnings of the previous generation), α is the intercept term representing the average change in the child's log earnings, and μ is a random error i.i.d. with a zero mean and is homoscedastic. The coefficient β is the intergenerational elasticity of offspring's earnings with respect to their father's earnings, and it is our parameter of interest.

Let ρ be the correlation between W_{it} and W_{it-1}; then β is related to ρ by the following equation:

$$\beta = \rho \frac{\sigma_{W_{it}}}{\sigma_{W_{it-1}}} \tag{7}$$

where σ is the standard deviation. In other words, the coefficient is related to the correlation between children's and fathers' log earnings. In particular, the coefficient β will be exactly equal to ρ when: $\sigma_{W_{it-1}} = \sigma_{W_{it}}$.

On one hand, when $\beta = 0$, children's earnings are not determined by their fathers' earnings. On the other hand, a value of $\beta = 1$ represents a situation of complete immobility, that is, children's earnings are fully determined by their fathers' earnings. Generally, the coefficient is between these two values. Therefore, to really evaluate if the coefficient is high or low, it is necessary to compare the results to those found for other countries.

If we had permanent income for successive generations in our sample, we would directly estimate equation 6 using the ordinary least square estimator without any problem. Unfortunately, we do not have this information in one data set.

First, most data sets only provide measures of current earnings and fail to provide measures of individual permanent income. Solon (1992) and Zimmerman (1992) show that the use of current earnings as a proxy for permanent earnings leads to downward OLS estimates of β. Different solutions can be implemented to reduce or eliminate this bias. If we work with panel data, we can calculate an average of current earnings over several years as a proxy of permanent income. Another possibility lies in using instrumental variables to estimate β. In this paper, in the case of the father's earnings, we estimate it by using auxiliary variables. Therefore, the estimated earnings is an average that can be considered as a proxy of the father's permanent earnings. In the case of children, we select adult ages as close as possible to the age in which earnings are similar to permanent income. In particular, Haider and Solon (2006) suggests the use of offsprings around 40 years old.

Second, we also have other selection problems that lead us to inconsistent estimations of β. In the next subsection, we describe the main selection problems that we face and how we solve them in this paper.

3.2 Sample selection problems

The estimation of intergenerational earnings mobility can frequently be biased due to different sample selection problems. The two most important selection problems we experience in short panels are co-residence selection and employment selection.[5]

Following Nicoletti and Francesconi (2006), we define co-residence selection to the fact that we only observe earnings for pairs of parents and children when they live together in at least one wave of the panel. On the contrary, we do not have information for sons and daughters who never co-reside with their parents during the panel. This selection problem could lead to an sub-estimation of the offsprings' earnings, since their living in the parental household is due to the fact they are still students or they do not have enough income to live emancipated. Thus, they are not a random sample. In general, this selection problem causes an overestimation of intergenerational mobility (an underestimation of the elasticity between parents' earnings and offsprings' earnings).

If the panel is long, we do not have to deal with this selection problem, as it is easy to observe young children living together with their parents and follow them to adulthood to know their earnings, except if they leave the panel (attrition problems) or if they do not have a job (employment selection).

In this paper we deal with this selection problem linking two samples as we will explain in the next subsection. We use one sample with information on adults and the characteristics (occupation, education, age) of the parents when the children are be-

[5]Only few papers on intergenerational mobility deal with these selection problems. For the employment selection, see, for example, Couch and Lillard (1998), Minicozzi (2003), Ermisch, Francesconi, and Siedler (2006), Nicoletti and Francesconi (2006). For the case of co-residence selection, there are fewer, see Couch and Lillard (1998), Comi (2003) and Nicoletti and Francesconi (2006).

tween 12 and 14 years old, and another sample with the same parental characteristics, but also with their earnings.

The **employment selection** refers to the problem wherein we only observe earnings for adults when they are employed; however, the decision to work or not to work is not random, especially in the case of women. Therefore, those who are working are a self-selected sample. Estimating intergenerational earnings mobility exclusively for those who are working yields biased estimators. We deal with this selection problem in the case of daughters by using the Heckman-type of correction estimation described in Vella (1998) and used in Ermisch, Francesconi, and Siedler (2006). In particular, the variables included in the selection equation are dependent children, marital status, age and father's earnings. In all regressions, these are good predictors of participation.

3.3 Intergenerational elasticity with sample selection

As we mention above, the co-residence selection problem can be solved if we have characteristics of the fathers because we can use them as auxiliary variables to impute their earnings. This is what we do when we use the two-sample two-stage least squares estimator (TS2SLS). This estimator is asymptotically equivalent to the two-sample instrumental variable estimator (2SIV) described by Angrist and Krueger (1992), Arellano and Meghir (1992) and Ridder and Moffit (2006).[6]

Both estimators are consistent under the assumptions described in Angrist and Krueger (1992). In particular, the two samples have to be independent random samples to guarantee consistency. Furthermore, the instrumental variables common to both samples have to be identically and independently distributed in the two samples.[7]

Since we do not have information of W_{it-1}, but do have a set of instrumental variables Z of W_{it-1}, we can estimate equation 6 in two steps. As we have explained before, we consider two independent samples: The first, which we call the main sample, has data on offspring log earnings, W_{it}, and characteristics of their fathers, Z, while the second, which we call the supplemental sample, has information on fathers' log earnings, W_{t-1}, and their age, education, and occupational characteristics, Z. In the

[6]For a detailed description of the properties of this estimator, see Arellano and Meghir (1992), Angrist and Krueger (1992) and Ridder and Moffit (2006).

[7]The two estimators are numerically identical in the case of a single sample; however, when combining two separate samples, the equivalence only holds asymptotically.

empirical application, we combine the supplemental and the main sample to estimate the intergenerational equation 6 by using the TS2SLS estimator.

In the first step, we use the supplemental sample to estimate a log earnings equation for fathers using, as explanatory variables, their characteristics, Z, that is:

$$W_{t-1} = Z_{t-1}\delta + v_i \tag{8}$$

In the second step, we estimate the intergenerational mobility equation 6 by using the main sample and replacing the unobserved W_{it-1} with its predictor,

$$\widehat{W_{it-1}} = Z_{it-1}\hat{\delta}, \tag{9}$$

where $\hat{\delta}$ are the coefficients estimated in the first step, and Z are the variables observed in the main sample. As Nicoletti and Ermisch (2007) point out, we can think of this method as a cold-deck linear regression imputation. Cold-deck refers to the fact that an external data source (the supplemental sample) is employed to estimate the coefficients used to impute the missing W_{it-1} in the main sample. Thus, we estimate equation 6 by using the imputed fathers' earnings.

$$W_{it} = \alpha + \beta(Z_{it-1}\hat{\delta}) + u_i \tag{10}$$

Equations 8 and 10 are estimated with ordinary least square estimator and standard error of the estimates of equation 10 are corrected for heteroscedasticity.[8] In order to take into account the life-cycle profiles, the estimation of both equations includes additional controls for individual's and father's ages.

The TS2SLS (2SIV) estimator is very similar to the classical IV estimator, using Z_{it-1} as instrumental variables, except for the fact that the first step estimates are taken from a different sample than in the second step.

In the previous studies that estimate intergenerational mobility combining two different datasets, different variables have been used to impute the missing father's earnings. For example, Björklund and Jäntti (1997) use father's education and occupation. Grawe (2004) uses only the education levels, while Fortin and Lefebvre (1998) uses only 16 occupational groups, which, as the authors admit, can affect the quality of the imputation of earnings for fathers. Lefranc and Trannoy (2004) instead use

[8]Heteroscedasticity is corrected by using the Huber White estimator.

eight different levels of education, seven occupational groups, and age. In Nicoletti and Ermisch (2007), the set of candidates as instrumental variables is also quite large, and the researchers try different combinations of the available instrumental variables .

Nicoletti and Ermisch (2007) express how important it is to choose instrumental variables that are strongly correlated with the variable to be instrumented because, if they are not, we will obtain inconsistent estimates. Therefore, we have to choose the instruments such that the R^2 of the regression can be as high as possible.

4 Data Sources and Sample Selection Rules

As we explained above, we combine two separate samples to estimate intergenerational earnings mobility, a main sample and a supplemental sample.

In our case, the main sample is the Survey of Living Conditions (Encuesta de Condiciones de Vida (ECV)) for the year 2005, that is, the Spanish component of the European Union Statistics on Income and Living Conditions (EU-SILC).[9]

The ECV has annually interviewed a sample of about 14,000 households representative of the Spanish households, and has keep each household in the sample for four years. Personal interviews are conducted at approximately one-year intervals with adult members of all the households.

From the ECV, we have information about adults' earnings and a set of characteristics of their fathers when they were between 12 and 14 years old.

Our supplemental sample is the Family Expenditure Survey of 1980-1981 (Encuesta de Presupuestos Familiares). This survey was designed with the purpose of estimating consumption and the weights of the different goods used in the consumer price index. In addition, we also have information regarding earnings, occupation, and the education level of the head of the household. Thus, in this sample we have data on the father's earnings and the same set of their characteristics that are available in the main sample.

Although we have the same characteristics in both samples, we have to recode some variables to have an homogenous classification across surveys.[10]

[9]The EU-SILC is an instrument that aims to collect timely and comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion, and living conditions. This instrument is anchored in the European Statistical System (ESS).

[10]For a detailed description of the frequencies of the different characteristics in the main and

Our main sample is composed by individuals, either the head of the household or the spouse of the household head, born between 1955 and 1975, self-employed or in paid employment, who report positive labour earnings and are full-time workers. Thus, in the year 2005, these adults were between 30 and 50 years old and they were 12 or 14 years old between 1969 and 1989. This is the reason we use the Family Expenditure Survey of 1980-1981 as the supplemental sample with which to estimate fathers' earnings.

We suppose that when the children were 12 or 14 years old, their fathers were between 37 and 57 years old. Thus, when we estimate the fathers' earnings regression we select males between those ages.

As we have mentioned above, one problem that can bias intergenerational mobility studies is measurement error with regard to earnings. Theoretically, we would like to consider the intergenerational elasticity in long-run permanent earnings, but we can observe earnings only in a single or a few specific years. Thus, the question is, what is the age at which the current earnings should be observed to provide a closest measure of permanent earnings? Haider and Solon (2006) show that it is reasonable to choose sons around age 40 and fathers with ages between 31 and 55. Therefore, assuming that these results hold for other countries, we choose similar age intervals in our empirical application.

After the exclusions, we have a total of 4,352 pairs, and in this sample, we have fathers and children employed that reported positive earnings.

The earnings variable we use in all the specifications is the log of current gross annual earnings, which is almost directly collected (not imputed), and is not distorted by the national taxation system.

Tables 1 and 2 present the principal descriptive statistics of our final sample of sons and daughters, respectively. Tables A.2 and A.3 in the Appendix show the transition matrices between fathers and children. These tables give us an intuitive vision of the persistence of earnings or education.

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supplemental samples see table A.1 in the Appendix.

Table 1: Descriptive statistics: Sons in the main sample after exclusions.

	sons 30-40	sons 40-50
Observations	1,334	1,322
annual earnings	19,728.35	22,403.7
log of annual earnings	9.72	9.84
Education		
Primary education	13.49%	19.48%
Secondary education (first step)	24.47%	25.00%
Secondary education (second step)	25.42%	24.59%
Vocational qualification	2.64%	1.73%
Higher education (university)	33.97%	29.21%
Occupation		
Higher-grade professionals	5.01%	6.6%
Higher-grade manager	11.65%	10.94%
Low grade professional	12.06%	9.97%
Routine non-manual employees high grade	7.99%	10.80%
Routine non-manual employees low grade	10.98%	9.28%
Skilled agriculture workers	2.37%	3.09%
Skilled manual workers	23.51%	22.70%
Low grade technician	12.33%	13.69%
Unskilled workers	14.09%	12.93%

5 Results

5.1 Main Results

In this section, we present the empirical results on intergenerational mobility estimation with corrections to the sample selection problems. As we have explained before, we use a two-sample two-stage estimation, whose first step consists of the estimation of the fathers' earnings regression using the supplemental sample. The results of this regression are presented in table 3. These coefficients are then used to impute the fathers' earnings in the main sample, since we have the same characteristics in both samples (main and supplemental). Therefore, in the second step, using the coefficients from the supplemental sample and the characteristics of the main sample, we estimate earnings for each father in the main sample.

Table 4 reports the second step, the coefficients of the intergenerational regression between annual children's earnings (sons and daughters) and the fathers' imputed earnings correcting the co-residence selection problem. In all columns, the father's predicted log earnings has a significant positive effect on child's earnings.

Table 2: Descriptive statistics: Daughters in the main sample after exclusions

	daughters 30-40	daughters 40-50
Observations	875	821
annual earnings	13,539.65	15,584.45
log of annual earnings	9.2	9.31
Education		
Primary education	10.39%	17.44%
Secondary education (first step)	19.95%	21.54%
Secondary education (second step)	21.78%	23.35%
Vocational qualification	2.35%	1.11%
Higher education (university)	45.52%	36.67%
Occupation		
Higher-grade professionals	1.59%	1.96%
Higher-grade manager	17.44%	19.54%
Low grade professional	11.68%	9.90%
Routine non-manual employees high grade	21.76%	16.89%
Routine non-manual employees low grade	21.08%	19.80%
Skilled agriculture workers	0.91%	0.85%
Skilled manual workers	4.85%	5.38%
Low grade technician	2.35%	1.71%
Unskilled workers	18.35%	23.98%

We estimate the elasticity for sons and daughters for two different cohorts, those whose ages are between 30 and 40 and those who are between 40 and 50 in 2005. For sons (first and second columns), regression coefficients are 0.38 for the first cohort and 0.42 for the second cohort. In the case of daughters (third and fourth columns), the elasticities are 0.50 and 0.58, respectively.

We observe smaller correlations for the younger cohorts. Therefore, the intergenerational mobility in Spain has increased, and the younger cohorts earnings are less correlated with father's as earnings compared to the older cohort.

By comparing the estimates for sons and daughters, we obtain a higher correlation for daughters. If we recall that our sample is restricted to full time workers, this result should not be surprising. It is likely that full time women workers are not a random group. The increase in female labour force participation in Spain began at the end of the 70s, but this participation is still presently lower than that of men. It is intuitive that full-time women workers are probably more common in some types of household (highly educated households or very poor households), thus the correlation is higher. It will be interesting to know if this difference between women and men is

Table 3: First step: estimates of father's earnings equation with the supplemental sample

Dependent variable	log father's earnings
age	0.0571 (0.0211)
age square	-0.0006 (0.0002)
Education	
Primary education	0.1873 (0.0148)
Secondary education (first step)	0.3919 (0.0276)
Secondary education (second step)	0.5254 (0.0326)
Vocational qualification	0.5581 (0.0487)
Higher education (university)	0.8455 (0.0281)
Occupation	
Higher grade manager	-0.4381 (0.0404)
Low grade professional	-0.0753 (0.0986)
Routine non-manual employees high grade	-0.0913 (0.0279)
Routine non-manual employees low grade	-0.3158 (0.0320)
Skilled agriculture workers	-0.8155 (0.0306)
Skilled manual workers	-0.1395 (0.0300)
Lower-grade technician	-0.2009 (0.0298)
Unskilled workers	-0.3177 (0.0285)
Constant	11.9961 (0.4918)
Obs	5929
R^2	0.402

Note: standard errors in parentheses. In **Education**: none (reference) and in **Occupation**: Higher-grade professionals (reference).

Table 4: Second Step: Intergenerational regression in annual earnings in the main sample

	sons 30-40	sons 40-50	daughters 30-40	daughters 40-50
father's earnings	0.380 (0.042)	0.427 (0.041)	0.504 (0.066)	0.582 (0.061)
age	0.140 (0.005)	0.022 (0.005)	0.028 (0.008)	0.010 (0.008)
Constant	4.258 (0.596)	3.315 (0.605)	1.829 (0.936)	1.513 (0.895)
Obs.	1334	1322	875	821
R^2	0.061	0.08	0.072	0.10

Note:Dependant variable is log of annual labor earnings. Fathers earnings refers to the log of father annual labor earnings. Robust standard errors in parentheses.

Table 5: Intergenerational earnings mobility for women correcting for employment selection

	daughters 30-40	daughters 40-50
father's earnings	0.369 (0.074)	0.498 (0.062)
age	0.043 (0.009)	0.009 (0.008)
Constant	3.285 (1.042)	1.287 (0.919)
Obs.	1025	992
R^2	0.072	0.10

Note:Dependant variable is log of annual labor earnings. Fathers earnings refers to the log of father annual labor earnings. Robust standard errors in parentheses.

still important when we correct for this employment selection.

In Table 4 we have reported the estimation of intergenerational earnings mobility, correcting only for the co-residence selection problem. Estimates in Table 4 assume that labour market participation is random; however, this participation, especially for women, is not random. In Table 5 we present the result of the estimation of equation 10 correcting for the employment selection in the case of daughters. We use the variables married, having children, father's earnings and age to predict selection. If we compare the two last columns of Table 4 with data from Table 5, we observe some differences. The elasticity between father's earnings and daughter's earnings is smaller when we correct for the employment selection with a Heckman selection model. Furthermore, the differences between sons and daughters disappear.

The figure of intergenerational earnings elasticity *per se* does not give a lot of information. It is always useful to compare our estimates of intergenerational earnings mobility in Spain with the results obtained for other countries. However, when we want to compare our results, we should be aware of the potential impact of differences in the definition of the children's sample and the estimation method applied.

For example, in the US, depending on the study considered, we can observe a wide range of elasticities, from 0.13 to 0.61. Solon (1999) provides an extensive survey of the US results obtained in the 90s and concludes that a reasonable guess of the intergenerational elasticity in long-run earnings for men in the United States is 0.4 or higher. This conclusion is obtained in studies using multi-year averages of father's and child's earnings, computed from panel data, as a measure of individual permanent income.

There are some studies that appear very close to our analysis because they use similar methodologies. One of these papers is Björklund and Jäntti (1997) for Sweden and the US. They find an elasticity of 0.52 for the United State and 0.28 for Sweden. Nicoletti and Ermisch (2007) apply the same methodology for Britain, obtaining an elasticity that ranges from 0.20 to 0.25 for sons. In the same way, Lefranc and Trannoy (2004) find an elasticity of 0.40 for sons and 0.30 for daughters. Furthermore, Mocetti (2007) show Italy as a very immobile society. In particular, he finds elasticities around 0.50. Thus, comparing these results with our estimations, we observe that Spain presents less intergenerational mobility than that of Sweden, and Britain, more than that of the United States and Italy and similar mobility than in France.

As Lefranc and Trannoy (2004) point out, one possible explanation for why Europe shows more intergenerational mobility than the United States is the way in which higher education is financed. In Spain, France, and Sweden the access to higher education is free, while in the United States payment of tuition may be a problem for poor households, even if generous grants are available for bright students.

Evidence available for other countries and surveyed by Solon (2002) suggest a rather high degree of intergenerational mobility in Finland (Österbacka (2001)) and Canada (Corak and Heisz (1999)), where the elasticity is around 0.2 or lower. There is some empirical evidence for Germany (see Couch and Dunn (1997)) that expresses a similar correlation to the United States.

Overall, we find an intergenerational correlation for Spain that ranks between a group of more mobile societies, including the Nordic countries, Canada, and Britain and a group of less mobile countries, which include the United States and Italy. We find an elasticity that is similar to France for sons; however, in the case of daughters we obtain larger elasticities than those found in France.

5.2 Decomposing the earnings elasticity

Two-sample instrumental variable estimation allows for a decomposition of the sources of earnings elasticity across generations. Using the decomposition developed by Bowles and Gintis (2002) and followed by Lefranc and Trannoy (2004), we can express offsprings' and fathers' earnings as:

$$W_{it} = Educ_i^c \ \delta_{educ}^c + Occup_i^c \ \delta_{occup}^c + \mu_i^c \quad for\ children's\ earnings \qquad (11)$$

$$W_{it-1} = Educ_i^f \ \delta_{educ}^f + Occup_i^f \ \delta_{occup}^f + \mu_i^f \quad for \ father's \ earnings \tag{12}$$

where the supra-indices c and f are used to identify children's and fathers' characteristics respectively. The variable $Educ$ is the individual's education, while $Occup$ is the individual's occupation; these are the variables we have used to estimate fathers earnings in the supplemental sample.[11]

Thus, the elasticity β is simply given by:

$$\beta = \frac{cov(W_{it} \ , \ Educ_i^f \delta_{educ}^f + Occup_i^f \delta_{occup}^f)}{V(Educ_i^f \delta_{educ}^f + Occup_i^f \delta_{occup}^f)}$$

Then, we can rewrite β as a decomposition of six terms:

$$\beta = \frac{1}{V(Educ_i^f \delta_{educ}^f + Occup_i^f \delta_{occup}^f)} \times \Big[\delta_{educ}^c cov(Educ_i^c, Educ_i^f)\delta_{educ}^f$$
$$+ \delta_{occup}^c cov(Occup_i^c, Occup_i^f)\delta_{occup}^f + \delta_{educ}^c cov(Educ_i^c, Occup_i^f)\delta_{occup}^f$$
$$+ \delta_{occup}^c cov(Occup_i^c, Educ_i^f)\delta_{educ}^f + cov(\mu_i^c, Educ_i^f)\delta_{educ}^f + cov(\mu_i^c, Occup_i^f)\delta_{occup}^f \Big]$$

Bowles and Gintis (2002) remark that it is important to consider this decomposition as a descriptive device and not as an analysis of causal effects.

The results of applying this decomposition to the estimation of earnings elasticity presented in table 4 are given in table 6

Table 6: Decomposition of earnings regression coefficient

	sons 30-40	sons 40-50	daughters 30-40	daughters 40-50
$educ_c - educ_f$	0.065	0.084	0.081	0.094
$occup_c - occup_f$	0.143	0.152	0.161	0.187
$educ_c - ocup_f$	0.080	0.082	0.105	0.110
$occup_c - educ_f$	0.055	0.071	0.098	0.107
$res_c - educ_f$	0.002	0.018	0.014	0.032
$res_c - occup_f$	0.035	0.020	0.045	0.052
total	0.380	0.427	0.504	0.582

As Lefranc and Trannoy (2004) observe, these results can be interpreted as, assuming that the only channel of intergenerational earnings correlation would work through

[11] In order to provide an easy exposition, the variable age is ignored here; however, it is taken into account in the empirical implementation of the decomposition.

the correlation of the fathers' and children's education, the elasticity coefficient for sons between 30 and 40 and fathers' earnings would be equal 0.065.

Table 6 shows that, for all ages and for both sons and daughters, the correlation between children's and fathers' occupations is the most important component for understanding the intergenerational elasticity between earnings. Furthermore, the correlation between the father's occupation and his offspring's educations is also important. If we add the influence of the father's occupation on his child's occupation and education, we explain almost half of the intergenerational elasticity coefficient. However, we can observe a slight contribution of the father's education. This should not be surprising, since the fathers of our sample, who now have adult children, have lower educational levels than do their offspring. Therefore, their occupations are probably better than the education as indicators of their social position for predicting their children's earnings. These results are in line with those obtained by Lefranc and Trannoy (2004) in the decomposition for France and by Österbacka (2001) for Finland. They find that the most important component of the intergenerational correlation in earnings is the correlation between fathers' and children's social positions.

5.3 Quantile regressions

When we regress the children's earnings on their father's earnings we provide a measure of intergenerational mobility at the mean; however, it could be interesting to explore if this correlation is similar or different at different points of the earnings distribution. If we have homoscedasticity, the coefficient estimated at each percentile will be not statistically different to the coefficient at the mean; however, in the presence of heteroscedasticity, we can obtain different coefficients. After testing the heteroscedasticity with the white test in our sample, we reject the null hypothesis of homoscedasticity.[12] Therefore, it could be interesting to estimate quantile regressions.

Are poor sons and daughters less or more determined by their father's earnings? If low-paid children are more influenced by their father's earnings than are children with higher salaries, then the intergenerational elasticity at the mean gives us an incomplete picture of the correlation between fathers' and children's earnings

By estimating quantile regressions, we have a more complete picture of intergenera-

[12] The results of this exercise are available from the author.

Table 7: Intergenerational mobility by quantiles

	Average	10th	25th	50th	75th	90th
sons 30-40	0.380	0.428	0.339	0.391	0.356	0.394
	(0.042)	(0.109)	(0.762)	(0.032)	(0.059)	(0.067)
sons 40-50	0.427	0.656	0.435	0.468	0.502	0.485
	(0.042)	(0.107)	(0.059)	(0.044)	(0.044)	(0.051)
daughters 30-40	0.504)	0.813	0.691	0.429	0.446	0.281
	(0.066)	(0.212)	(0.124)	(0.108)	(0.065)	(0.056)
daughters 40-50	0.582	0.938	0.864	0.724	0.641	0.410
	(0.061)	(0.177)	(0.064)	(0.067)	(0.081)	(0.069)

Note: Standard error for the estimated coefficients are in parenthesis. Average refers to mean regression, whereas q-th indicates the q-th percentile regression.

tional transmission of earnings because we have information of the correlation between children's and parents' earnings at different points of the distribution of the children's earnings.[13]

Mean regressions explain how the conditional mean of the children's earnings depend on parents' earnings; however, quantile regressions explain how children earnings depend on parents earnings at each specific quantile of the conditional distribution of the children' earnings given the fathers' earnings.

In table 7, we can observe the coefficient of the father's log earnings at different points of the children's earnings distribution. In the first column, we show the mean regression, which tells us how important father's earnings are on average. In the rest of the columns, quantile regressions evaluate the influence of father's earnings at each specific quantile. We consider the 10th, 25th, 50th, 75th and 90th percentiles. We can observe that the influence of father's earnings is greater as we move to the poorest quantiles of the distribution. Thus, mobility is lower for the children born in disadvantaged families. This pattern is particularly observed in the case of daughters, where we can observe a monotonic decrease of the elasticity between fathers' and daughters' earnings as we move to the richer percentiles. The results are in-line with those obtained by Nicoletti (2008) for father's and daughter's occupations in Britain. For sons, we obtain the highest elasticity at the 10th percentile. Thus, we also observe low mobility for poor sons. However, when we move to richer percentiles the pattern

[13]Quantile regression is a statistical technique introduced by Koenker and Bassett (1978) that allows us to estimate conditional functions by quantiles, at different points of the distribution.

is no longer monotonic, and the coefficients are quite close between them and similar to the coefficients in the mean regression.

6 Final remarks

In this paper we analyse the intergenerational earnings mobility in Spain solving the co-residence and the employment selection problems. Since there is no Spanish survey with information on children and their fathers' earnings covering a long period, we deal with the co-residence selection using two separate samples: a main sample containing information on children's earnings and a set of characteristics of the fathers, and a supplemental sample with the same characteristics for the fathers and their earnings. We combine the two samples by using the two-sample two-stage least square estimator.

When we only correct for the co-residence selection problem we find an elasticity of 0.38 for sons between 30 and 40 years old, an elasticity of 0.42 for sons between 40 and 50 years old. In the case of daughters, we obtain elasticities of 0.50 and 0.58, respectively. We observe smaller correlation for the younger cohorts. Therefore, the intergenerational mobility has increased in Spain. Younger cohorts' earnings are less correlated with father's earnings as compared with the older cohort.

By comparing the estimates for sons and daughters, we obtain higher correlations for daughter. However, since the participation in the labour market is not random, especially for women, we estimate the earnings elasticity between daughters and fathers correcting for the employment selection with the Heckman selection model. The elasticity between father's earnings and daughter's earnings is smaller when we correct for employment selection and the differences between sons and daughters disappear.

By decomposing the sources of earnings correlations, we find that the correlation between children's and father's occupation is the most important component to understand the intergenerational elasticity between earnings. Furthermore, the correlation between father's occupation and offspring's education is also important. Adding the influence of father's occupation on children's occupation and on children's education we explain almost half of the intergenerational elasticity coefficient. This should not be surprising since the fathers of our sample, who now have adult children now, have lower educational level than their offsprings. Thus, probably, their occupations are better than education as indicators of their social position in order to predict children's earnings.

Finally, estimating the elasticity between children's and father's earnings by quantiles, we find that the influence of the father's earnings is greater when we move to the lower tail of the distribution, especially for daughters' earnings. Thus, mobility is lower for the children born in disadvantaged families.

According to our findings, Spain shows a degree of intergenerational earnings mobility that is similar to France, lower than in the Nordic countries and in Britain and higher than in the United States and in Italy.

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Appendix

Table A.1: Distribution of father's education and occupation an coincidences between supplemental and main sample

	supplemental sample	main sample
Observation	5,032	4,352
Education		
No finish primary education	23.82	20.09
Primary education	51.28	57.65
Secondary education (first step)	8.46	6.08
Secondary education (second step)	5.90	5.84
Vocational qualification	2.07	0.49
Higher education (university)	8.47	9.85
Occupation		
Higher grade professionals	9.25	8.04
Higher grade manager	4.28	3.70
Low grade professional	3.43	5.58
Routine non-manual employees high grade	11.04	6.18
Routine non-manual employees low grade	9.85	7.25
Skilled agriculture workers	12.74	12.85
Skilled manual workers	15.88	24.99
Lower-grade technician	13.81	11.82
Unskilled workers	19.71	19.60

Note: All frequencies are weighted using the respective sampling weights.

Table A.2: Transition matrices of earnings between fathers and child

		Quantil of the father				
		1	2	3	4	5
Quantil of the son or daughter	1	30,08%	23,93%	16,98%	16,20%	13,23%
	2	24,40%	22,34%	19,17%	18,29%	16,20%
	3	19,12%	23,54%	20,26%	21,67%	15,66%
	4	15,74%	15,69%	22,64%	23,26%	22,41%
	5	10,66%	14,50%	20,95%	20,58%	32,49%

Table A.3: Transition matrices of education between fathers and child

		Education of the father					
		0	1	2	3	4	5
Education of the child	1	34,07%	13,89%	4,85%	3,04%	0,00%	0,60%
	2	34,77%	23,72%	18,12%	7,43%	8,00%	3,99%
	3	17,98%	25,22%	34,30%	31,42%	36,00%	16,37%
	4	1,90%	2,18%	1,94%	1,01%	12,00%	1,00%
	5	11,29%	34,98%	40,78%	57,09%	44,00%	78,04%

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