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

María Cervini Plá †

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Abstract

This paper analyses the extent of intergenerational earnings mobility in Spain considering some sample selection problems, like co-residence and employment selection. We deal with the co-residence selection problem considering two separate samples: a main sample containing information on offsprings' earnings and a set of occupational and education characteristics of their fathers and a supplemental one with data on the same set of fathers' characteristics and their earnings. We combine information from the two samples by using the two-sample two-stage least square estimator. We find a small decrease in the elasticity when we move to younger cohorts. Furthermore, we find a high correlation in the case of daughters. However, when we take into account the employment selection in the case of daughters adopting a Heckman-type correction method, the difference between sons and daughters vanish. Decomposing the sources of earnings elasticity across generations I find that the correlation between children's and father's occupation is the most important component. 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.

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

JEL classification: D31, J31, J62.

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†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 socioeconomic achievements of parents and those of their children. If we believe that equal opportunity is a desirable characteristic of a good society, a high degree of intergenerational mobility will be an important indicator of the healthiness and success of a society. In this context, children are not predetermined by their parents. Children from different families have equal options regarding investments in their human resource and their expected incomes. (Behrman and Taubman (1990)).

Intergenerational mobility studies usually estimate the correlation between socioeconomic status of parents and their offsprings. A high correlation would imply that people born in disadvantaged families have a smaller chance to occupy the highest socio-economic positions than people born in privileged families. A zero correlation would imply instead a high degree of mobility and more equal opportunities. Economist have mainly concentrated on the relation between fathers and off-springs' permanent income, ie, intergenerational elasticity in continuous monetary variables, typically income or earnings, while sociologists use association measures between ordered categorical variables such as social and economic class positions.[1]

In this paper, following the economic approach, we focus on intergenerational mobility measured by the intergenerational elasticity of offsprings' earnings with respect to their fathers' earnings.

The main objective of this paper is to study the extent and evolution of intergenerational earnings mobility in Spain considering some sample selection problems, like co-residence and employment selection.

In general, in a panel we have information of 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]

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

[2]Nicoletti and Francesconi (2006) analyze intergenerational mobility using an occupational prestige score. They find that the β coefficient (in this case β represents the elasticity between father's and

This selection problem is particularly important in Spain, where we only have short panels, so we do not have information on both children and their fathers' earnings belonging to very distant cohorts and when the children is an adult and earn a salary similar to his permanent earning.

How do I deal with this problem? It is possible to estimate consistently intergenerational earnings mobility using the two-sample two-stage least square estimator.[3] This method combine 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 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. In particular my two samples are: the Spanish sample of the EU-SILC, called Survey of Living Conditions (Encuesta de Condiciones de Vida (ECV)) and the Household Budget Survey of 1980-1981 (Encuesta de Presupuestos Familiares (EPF)). In the ECV we observe sons' (respectively daughters') earnings and a set of occupational characteristics of their parents when the children were aged between 12 and 16. This gives us a set of auxiliary variables, such as education dummies, age, occupational sector, which can be used to predict the parents' missing earnings. Since the participation of women in the labour market has increased since the eighties, for the case of parents I will only consider fathers' earnings. Thus, I estimate the elasticity between offspring's earnings and fathers' earnings.

The second problem I try to correct is the **employment selection**. That is mean, with the problem that we only have earnings for adults it they are employed. Since the decision to work or not work is not random, especially in the case of women, estimate intergenerational earnings mobility only for those who are working give us biased estimators. How do I deal with this selection problem? For daughters, we use a Heckman-type of correction estimation described in Vella (1998) and used in Ermisch, Francesconi, and Siedler (2006), which is based on exclusion restriction.

offspring's occupational prestige score) is underestimated when they only consider the pairs of children and parent that are co-resident.

[3] This method was developed by Arellano and Meghir (1992) and Ridder and Moffit (2006) and has been already applied to study intergenerational mobility by Björklund and Jäntti (1997) in Sweden, Fortin and Lefebvre (1998) in Canada, by Grawe (2004)) in Ecuador, Nepal, Pakistan and Peru, by Lefranc and Trannoy (2004) in France and by Nicoletti and Ermisch (2007) in Britain.

In Spain the study of intergenerational mobility has been undertaken mainly by sociologist. For example, Carabaña (1999) studied occupational mobility. From an economic point of view, there are some studies of intragenerational mobility like Cantó (2000), Rodriguez, Salas, and García (2002) and Ayala and Sastre (2002a, 2002b). These studies analyse the probability that one individual could change her level of income during her life. The only study for Spain that analyzes intergenerational mobility, as far as I know, is Hugalde (2004). She analyzes the intergenerational income and education mobility using the Household Budget Survey (Encuesta de Presupuestos Familiares) for 1980 and 1990. However she only estimates the elasticity when the child and her father live together. She finds an elasticity of income for the year 1990 of 0.44.

Thus, the main contribution of this paper is analyze intergenerational earnings mobility in Spain for all adults, those who live and those who do not live with their parents. Another important contribution of my paper is considering also the employment selection. So, I take into account the two major selection problems of the short panel together. Furthermore, we investigate more of the characteristics of this earnings transmission doing two exercise, first we do a decomposition of the sources of earnings elasticity and the second we investigate the influence of father's earnings by quantiles.

When we correct for the co-residence selection problem I 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 I obtain elasticities of 0.50 and 0.58 respectively. Thus, we find a slightly lower elasticity when we move to younger cohorts. Furthermore, we obtain more elasticity for daughters. However, when I consider the employment selection on women the differences disappear. Decomposing the sources of earnings correlations I find that the correlation between children's and father's occupation is the most important component. Father' occupation is a good indicator of his social position and a better indicator than education to predict children's earnings. Finally, we estimate 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 in the case of daughters. Comparing the elasticities obtained in Spain with the results for other countries, I find that the intergenerational mobility in Spain is similar to France, lower than the Nordic countries and Britain and higher than the United States.

The rest of the paper is organized as follows. In the next section I briefly describe the main sources of earnings transmission. In section 3 I present a theoretical framework that allow us to understand some of the sources of earnings transmission between generations. Section 4 describes how I implement the two-sample two stage least square estimator. In section 5 I describe the data source, the selection sample and the variables used in the empirical analysis. Section 6 reports the results and finally, section 7, concludes with some final remarks.

2 Sources of earnings transmission

Why some children achieve success when they become adults while others do not? Why some children obtain better jobs and higher earnings? Which are the channels trough 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 through institutions it also affects the intergenerational mobility.

Here I will summarize the main channels of earnings transmission. Although most of these channels are the same when we analyze the transmission of income, here I will concentrate on the persistence of earnings.

One of the most important channels of intergenerational earnings transmission derives from education. Educational choices are conditioned by individual unobserved ability (labeled talent), family cultural background, family financial resources, public resources and- more generally- social capital. As Checchi (2006) points out, most of these factors exhibit intertemporal and intergenerational persistence.

Ability is passed on to children via heredity (genetic endowment). Ability can influence the education attainment and thus earnings or can influence earnings directly through the type of job obtained.

Education attainment also depends on cultural influences. There is a vast empirical evidence about how children of educated parents are more likely to acquire education. This may be partly due to parent imitation (if they see their parents reading a book, they get the idea that reading is a good activity), 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/her children to achieve more at school. In addition, if the educational system is not homogeneous, an educated parent always has some advantage in collecting information about school quality, and can reorient his/her child's choices towards better opportunities. A strengthening factor derives from marital choices: as long as there is assortative mating (namely, better-educated persons preferring to pair with other educated persons), the cultural background within a family is made more homogeneous, and the influences received by each parent reinforce one another.

Although it is very difficult to separate traits that are genetic from traits that are culturally induced, the empirical evidence obtained from the sample of twins indicates that the relative contribution from genetics to intertemporal persistence is low. Bowles and Gintis (2002) show that measured IQ test score contributes little to earnings, and use this evidence to conclude that their contribution to intergenerational persistence must be low.

Furthermore, if access to education is limited by family financial resources due to liquidity constraints, and acquired education gains access to higher-paid jobs, this opens the door to a poverty trap: poor families are prevented from investing in the education of their children by a lack of resources and the inability to access financial markets, their children remain uneducated and poor, and thus they are unable to invest in their grandchildren either.

Another source of intergenerational earnings persistence emerges from territorial segregation, and is related to family wealth. If residential choices are influenced by the evaluation of local school quality, and school quality affects house prices, then richer families will gain access to better schools by locating closer to them. Better school quality combined with a more homogeneous cultural neighbourhood will yield greater social capital, thus providing a clear advantage to children raised in that environment. Thus, the neighbourhood can influence earnings through education (better schools) or through social capital (good neighbours allow me to obtain betters jobs).

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

3 Theoretical framework

Following Checchi (2006) and Lefranc and Trannoy (2004) I present here a simple model that allow us to understand better some of the sources of intergenerational earnings transmission.

Let us suppose an individual belonging to the family i and to generation t whose permanent earnings W_{it} derive 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 predetermined with respect to labour market status, and therefore with respect to earnings. If we consider that ability increases labour productivity, we should observe that:

$$W_{it} = \beta E_{it} + \varepsilon A_{it} + \mu_{1it} \tag{1}$$

Where the relationship between earnings, education and ability is assumed linear for simplicity and μ_{1it} is an i.i.d. error term, capturing the idea of luck in the labour market.

Taking into account the channels of intergenerational earnings transmission described in the previous section, we will consider four potential channels through which one generation may influence the following one. First, if ability is genetically (or mechanically) inherited, we indicate this effect with the α and $t-1$ represent the previous generation, so we have:

$$A_{it} = \delta + \alpha A_{it-1} + \mu_{2it} \tag{2}$$

This effect can be thought of as all aspects of earnings determinants that "money can't buy" and at the same time are transmitted from one generation to the next. For example, transmission of IQ, social network or preferences.

Second, education can be determined by the cultural influence of the family (described by the η). Third, if there are liquidity constraints, education is also determined by the family incomes, reducing the optimal investment on education by poor families. The intuition behind this effect is that investment in child's human capital, and more generally child's upbringing, is likely to be constrained by parental resources, in the presence of imperfect capital markets. For example Becker and Tomes (1979) assume that children endowment in human capital are chosen by their parents as a result of optimal allocation of the parents' permanent income. Parents' utility depends on parents' own consumption and children's permanent income.

We indicate this channel with the γ and we write

$$E_{it} = \eta E_{it-1} + \gamma Y_{it-1} \tag{3}$$

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

Forth, we consider the possibility that family networking and neighbourhood effects give access to better job opportunities. We indicate this channel with the θ, and we can extend equation 1 with an additional term:

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

Taking into account all this 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 on earnings. It is important to note that in a simple regression of child's earnings on parents's earnings, the coefficient will capture all these effects "that money can buy" together. Hence standard estimates of intergenerational earnings regression will provide an upward biased estimate of the causal effect of father earnings on child's earnings. Concretely we will estimate:

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

From a policy point of view, the distinction between the different components matters to predict the impact of economic policies or to know which policy could be better to improve mobility.

4 Estimation method

4.1 The econometric model

As I explained above, following the economic approach, I 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 identically and independently distributed (i.i.d.) with zero mean and homoskedastic. 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. Moreover, β is exactly equal to ρ when: $\sigma_{W_{it-1}} = \sigma_{W_{it}}$.

A coefficient β equal to zero indicates a situation where all children have "equal opportunities". When $\beta = 0$ all children have an average log earnings equal to α. When β is instead different from zero, offsprings' average log earnings depend also on their fathers' earnings.

On the other hand, a value of $\beta = 1$ indicates a situation of complete immobility, whereby (apart of the influence of ε) the children's position in their status distribution is fully determined by their father's position.

As Lefranc and Trannoy (2004) point out the elasticity concept seems more in tune with what economists would like to measure. For example, suppose that some policy reduces all income deviations from child's generation mean by the same factor. We hope to conclude that the inheritage of parental income has decreased with such a policy. In this situation the correlation coefficient remains invariant, meanwhile the elasticity coefficient decreases.

If I had permanent income for successive generations in our sample, I would estimate equation 6 using ordinary least square directly without any problem. Unfortunately I 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 earning as proxy for permanent earnings leads to downward OLS estimates of β. Different solutions have been implemented to reduce or eliminate this bias. One possibility is to work with panel data on fathers earnings and consist in using an average of father's current earnings over several years as a proxy of permanent income. Another alternative consist in using instrumental variables to estimate β. In this paper, in the case of father's earnings, I estimate it using auxiliary variables; and in the case of children, I select adult ages to estimate the elasticity trying to estimate the intergenerational earnings mobility as close as possible to the age in which earnings are similar to the permanent income.

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

4.2 Sample selection problems

Frecuently the estimation of intergenerational earnings mobility can be biased due to different sample selection problems.

The two most important selection problems I have in short panels are the co-residence selection and the selection into employment.[4]

Following Nicoletti and Francesconi (2006), I call **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 and we do not have information for adult sons

[4]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 indeed there are fewer, see Couch and Lillard (1998), Comi (2003) and Nicoletti and Francesconi (2006).

and daughters who never co-reside with their parents during the panel. This selection problem could lead to an under-representation of the real earnings adults offspring have because if they continue living in the parental house probably is because they are still student or they do not have enough earnings to live independently. 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 because 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 job (employment selection).

In this paper we deal with this selection problem linking two samples as I will explain in the next subsection. One sample with information on adults and characteristics (occupation, education, age) of the parents when the children are 14 years old and another sample with the same parents' characteristics but with their earnings.

The **employment selection** refers to the problem that we only have earnings for adults when they are employed. However, the decision to work or not work is not random, especially in the case of women. Thus, those who are working constitute a self-selected sample. Estimate intergenerational earnings mobility only for those who are working give us biased estimators. For daughters, we deal with this problem using a Heckman-type of correction estimation described in Vella (1998) and used in Ermisch, Francesconi, and Siedler (2006), which is based on exclusion restriction. 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.

4.3 Intergenerational elasticity with sample selection

As we express above the co-residence selection problem can be solved if we have characteristics of the fathers, because we can use these characteristics as auxiliary variables to impute his earnings. This is what we do when we use the two-sample two-stage least squares (TS2SLS).

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

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

where $\hat{\delta}$ are the coefficients estimated in the first step while Z are the variables observed in the main sample. This method can be viewed 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. This method was first proposed by Klevmarken (1982). 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 OLS and standard error of the estimates of equation 10 are corrected for heteroscedasticity.[5] To take into account the life-cycle profiles, estimation of both equations include additional controls for individual's and father's age. This estimation procedure is very similar to the IV estimation, using Z_{it-1} as instrumental variables, except for the fact that the first step estimates are taken from a different sample than the second step.

This estimator is asymptotically equivalent to the 2SIV (two-sample instrumental variable) estimator described by Angrist and Krueger (1992), Arellano and Meghir (1992) and Ridder and Moffit (2006). Both estimators are consistent under the assumptions described in Angrist and Krueger (1992). In particular both estimators

[5]Heteroscedasticity is taken into account using the Huber White estimator.

are not consistent if the two samples used are not two independent random samples. Moreover, the instrumental variables common to both samples have to be identically and independently distributed in the two samples. Instrumental variable estimator is numerically identical to the two-stage least squares.[6]

The variables used to impute the missing father's earnings, in some previous papers that estimate intergenerational mobility combining two different datasets, was dictated by the available variables. 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) use instead 8 different levels of education, 7 occupational groups and age. In Nicoletti and Ermisch (2007), the set of candidates as instrumental variables is also quite large and they try different combinations of the instrumental variables available.

Bound, Jaeger, and Baker (1995) express how important is to choose instrumental variables that are strongly correlated with the variable to be instrumented because if they are not, we will obtain inconsistency estimation. This suggest choosing instruments such that the R^2 of the imputation regression be as higher as possible.

Nevertheless, in our case, in contrast to Bound, Jaeger, and Baker (1995), the variable to be instrumented, the fathers' log earnings W_{it-1}, is exogenous or at least assumed so. In other words W_{it-1} is independent of u and u is independent of v. Under this assumptions, the ordinary least squares (OLS) estimation of the intergenerational mobility equation produces consistent estimators. The reason why we use the TS2SLS estimator is to combine two separate samples to solve the problem of missing W_{it-1}. The consistency of the TS2SLS (2SIV) estimator requires that $\widehat{W_{it-1}}$ be exogenous.

Nicoletti and Ermisch (2007) also discuss what happens when the instruments are endogenous. They arrive to the conclusion that the well-known rule for the choice of the instruments still applies. Instruments should be independent of u and with maximum multiple correlation with W_{it-1}, that is such that R^2 be maximum.

[6]The two types of estimators produce mathematically the same estimated coefficients when using a single sample, their equivalence holds instead only asymptotically when combining two separate samples. In our estimation procedure we use the TS2SLS to estimate the intergenerational mobility equation, but we consider standard error properly estimated to take account of the replacement of X with its prediction, see Arellano and Meghir (1992).

5 Data Sources and Sample Selection Rules

As we explained above, we combine two separate samples to estimate intergenerational 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).[7]

The ECV has annually interviewed a representative sample of about 14,000 households, keeping each household 4 years in the sample. Personal interviews are collected, at approximately one-year intervals, for adult members of all households.

From ECV we have information about son's and daughter's earnings and a set of characteristics of their fathers when the children were between 12 and 14 years old.

My supplemental sample is the Household Budget Survey of 1980-1981 (Encuesta de Presupuestos Familiares). This survey was designed with the aim of estimating consumption and the weights of the different goods used in the consumer index price. But, we also have, for the head of household, information about earnings, occupation and education level. Thus, in this sample we have data on father's earnings and the same set of their characteristics as we have 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.[8]

We consider the main sample given by individuals, either head of household or 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 they were between 30 and 50 years old and they were 12 or 14 years old between 1969 and 1989. This is the reason I use the Household Budget Survey of 1980-1981 as supplemental sample to estimate father's earnings.

We suppose that when the children are 12 or 14 years old, the fathers are between

[7] The EU-SILC is an instrument aiming at collecting 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). The EU-SILC was launched in 2004 in 13 Member States (BE, DK, EE, EL, ES, FR, IE, IT, LU, AT, PT, FI and SE) and in NO and IS. This first release of the cross-sectional data mainly refers to income reference year 2003 with a fieldwork carried out in 2004. The EU-SILC will reach its full scale extension with the 25 Member States plus NO, IS in 2005. It will later be completed by TR, RO, BG and CH.

[8] For a detailed description of the frequencies of the different characteristics in the main and supplemental sample see table A.1 in the Appendix.

37 and 57 years old. Thus, when we estimate the earnings father's regression we select males between those ages.

As I explained above one problem that can bias intergenerational mobility studies is measurement error in earnings. Theoretically, we would like to consider the intergenerational elasticity in long run permanent earnings but earnings can be observed only in a single or few specific years. The question is then, which is the age at which the current earnings should be observed to provide a proper measure of permanent earnings? Looking at the results in Haider and Solon (2006) and assuming that similar results hold for other countries, it seems reasonable to choose sons around age 40 and fathers with an age between 31 and 55. In our empirical application I follow this suggestion.

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

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%

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

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%

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 matrix between fathers and children. These tables give us an intuitive vision of the persistence of earnings or education.

6 Results

6.1 Main Results

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

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).

sample.

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

We estimate the elasticity for sons and daughters for two different cohorts, those whose age are between 30 and 40, and also for the cohort born between 1955 and 1965, those who are between 40 and 50 in 2005. For sons (first and second columns), regression coefficients are around 0.40 and for daughters (third and fourth columns) are around 0.54.

We observe smaller correlation for the younger cohorts. There are two possible explanations for this fact. The first one, is that for younger cohort we do not observe the permanent earnings because they are at the beginning of the working career. The second hypothesis is that in Spain the intergenerational mobility has increased. Thus,

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.

the younger cohorts earnings are less correlated with father's earnings compared with the older cohort.

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. Probably the full time women workers are not a random group. The increase in female labour force participation in Span began at the end of seventies but although now this participation is lower than in the case of men. It is intuitive that in full time women workers are probably more common in some types of household (high educated household or very poor household), thus the correlation is higher. It will be interesting to know if this difference between women and men is still important when we correct for this employment selection.

In table 4 I 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 I present the result of the estimation of equation 10 correcting for the employment selection in the case of women. I use the variables married, having children and father's earnings and age to predict selection. If we compare the two last columns of table 4 with 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 number of intergenerational earnings elasticity *per se* does not give a lot of information. Always it is useful compare our estimation of intergenerational earnings mobility in Spain with the results obtained for other countries. However, when we

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.

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 nineties and conclude that a reasonable guess of the intergenerational elasticity in long-run earnings for men in the United States is 0.4 or a bit higher. This conclusion is obtained in studies using multi-year averages of father and child earnings, computed from panel data, as a measure of individual permanent income.

A study that appears very close to ours, both in terms of sample definition and method used is the paper of Björklund and Jäntti (1997). They find an elasticity of 0.52 for the United State and 0.28 for Sweden. Nicoletti and Ermisch (2007) applying the same methodology for Britain, obtain 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. Thus, comparing these results with our estimations, we observe that Spain presents less intergenerational mobility than France, Sweden and Britain but more than the United States.

One possible explanation why Europe shows more intergenerational mobility than the United States is the way higher education is financed. In Spain, France, Sweden the access to higher education is free, while in the United State payment of tuition may be a problem for poor household, even if generous grants are available for bright students.

But clearly this is not a definite answer, our results should be confirmed and improved using more years of the main sample to obtain a better proxy for permanent child's earnings.

Evidence available for other countries and surveyed by Solon (2002) suggests 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. We find an elasticity that is similar to France for sons. However, in the case of daughters I obtain larger elasticity than in France.

6.2 Decomposing the earnings elasticity

The 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 offspring's and father's earnings as:

$$W_{it} = Educ_i^c \ \delta_{educ}^c + Occup_i^c \ \delta_{occup}^c + v_i^c \quad for\ children's\ earnings \tag{11}$$

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

where the supra-index c and f are used to identify children's and father's characteristics respectively. The variable *Educ* is the individual's education and *Occup* is the individual's occupation, these are the variables we have used to estimate fathers earnings in the supplemental sample.[9]

Thus, the elasticity β is simply given by:

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

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

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

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

It is important to notice that this decomposition should be seen as a descriptive device along the lines suggested in Bowles and Gintis (2002) 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) point out, these results can be interpreted as: assuming that the only channel of intergenerational earnings correlation would work through the correlation of father's and child's education, the elasticity coefficient for sons's between 30 and 40 and father's earnings would be equal 0.065.

The table 6 shows that for all ages and for both sons and daughters the correlation between children's and father's occupations 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. If I add the influence of father's occupation on children's occupation and on children's education I explain almost half of intergenerational elasticity coefficient. However, we can observe a little contribution of the father's education. This should not be surprising since the fathers of my sample, who have adults children now, are no so educated compared with his offspring. Thus, probably, their occupations are better indicators of their social position than education to predict children's earnings. These results are in line with those obtained by Lefranc and Trannoy (2004) in the decomposition to France and by Österbacka (2001) for Finland. They find that the bulk of the intergenerational correlation in earnings arise from the correlation between fathers and children social position.

6.3 Quantile regressions

When we regress the children's earnings on their parent's earnings we provide a measure of intergenerational mobility at the mean. However, it could interesting explore if the correlation between father's and children's earnings is similar or different at different points of the earnings distribution. Are poor sons and daughters less or more determined by father's earnings? If the effect of having an increase in the parents log earnings is better for children with lower salaries than children with higher salaries, then the intergenerational elasticity as a mean only gives partial information of the correlation between parents and children.

Estimating quantile regressions, we have a more complete picture of intergenerational transmission of earnings because we have information of the correlation between children's and parent's earnings at different points of the distribution of the children's earnings.[10]

Mean regressions explain how the conditional mean of the children 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 children earnings given father earnings. If we have homoscedasticity the coefficient estimated at each percentile will be not statistically different to the coefficient in the mean regression. However, in the presence of heteroscedasticity we can obtain different coefficient. After testing the heteroscedasticity with the white test in our sample we reject the null hypothesis of homoscedasticity. The results are presented in the Appendix.

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 tell us how important father's earnings are on average. The rest of the columns quantile regressions evaluate the influence of father's earnings at each specific

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

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.

quantile. I consider the 10th, 25th, 50th, 75th and 90th percentiles. We can observe that the influence of father's earnings is greater as soon as we move to the poorest quantiles of the distribution. Thus, the mobility is lower for the children born in disadvantaged families. This pattern is particulary observed in the case of daughters, where we can observe a monotonic decrease of the elasticity between fathers' and daughters' earnings as soon as we move to the richer percentiles. The results are in line to those obtained by Nicoletti (2008) for father's and daughter's occupations in Britain. In the case of son we obtain the highest elasticity at the 10th percentile. Thus, we also observe low mobility for the poor sons. However, when we move to the richer percentiles the pattern is not longer monotonic and the coefficients are quite close between them and similar to the coefficient in the mean regression.

7 Final remarks

In this paper I analyze the intergenerational earnings mobility in Spain considering some sample selections problems, as, for example, co-residence and employment selection. 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 considering two separately 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.

On average we find an elasticity around of 0.40 for sons and around 0.55 for daughters. We also observe smaller correlation for the younger cohorts. There are two possible explanations for this fact. The first one, is that for younger cohort we do not observe the permanent earnings because they are at the beginning of the working career. The second hypothesis is that in Spain the intergenerational mobility has increased. Thus, the younger cohorts earnings are less correlated with father's earnings compared with the older cohort.

Comparing the estimates for sons and daughters we obtain a higher correlation for daughters. 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 a 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 vanish.

Decomposing the sources of earnings correlations I 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 I explain almost half of intergenerational elasticity coefficient. This should not be surprising since the fathers of my sample, who have adults children now, are no so educated compared with his offspring. Thus, probably, their occupations are better indicators of their social position than education 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, the 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 the Nordic countries and Britain and higher than the United States.

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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%