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# Intergenerational earnings and income mobility in Spain

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## Abstract

This paper contributes to the large number of studies on intergenerational earnings and income mobility by providing new evidence for Spain. Since there are no Spanish surveys covering long-term information on both children and their fathers' income or earnings, we deal with this selection problem using the two-sample two-stage least squares estimator. We find that intergenerational mobility in Spain is similar to France, lower than in the Nordic countries and Britain and higher than in Italy and the United States. Furthermore, we use the Chadwick and Solon (2002) approach to explore the intergenerational mobility in the case of daughters overcoming employment selection, and we find similar results by gender.

**Keywords:** Intergenerational earnings and income mobility, two sample two stage least squares estimator, Spain.

**JEL classification:** D31, J31, J62.

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# 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 society, a high degree of intergenerational mobility is an important indicator of the health and success of society. In this context, the socioeconomic status of children from different families are not predetermined by their parents and they have equal options to achieve education and higher earnings (Behrman and Taubman (1990)).

Intergenerational mobility studies usually estimate the correlation between the socioeconomic status of parents and their offspring. On the one hand, a high correlation would imply that people born in disadvantaged families have a smaller chance to occupy the highest socioeconomic 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. Sociologists explore the association measures between ordered categorical variables, such as social and economic class position. Meanwhile the economics literature has primarily concentrated on the relationship between parents' and their offspring's permanent incomes or earnings.<sup>1</sup> In particular, the standard measure of intergenerational mobility that economists use is earnings or income elasticity.

In this paper, we contribute to the empirical literature by estimating the earnings and income mobility for Spain. In general these type of papers estimate the elasticity only for sons to avoid the typical employment selection of daughters. Therefore, another important contribution of our paper is to explore the intergenerational earnings mobility for daughters.

The estimation of intergenerational mobility can be biased due to different sample selection problems. One of these problems arises from the fact that, in a panel, we have information regarding offspring's 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.<sup>2</sup> This selection problem is particularly important in

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<sup>1</sup>See Solon (1999), Björklund and Jäntti (2000), Bowles and Gintis (2002), Erikson and Goldthorpe (2002) for a review.

<sup>2</sup>Nicoletti and Francesconi (2006) refer to this sample selection problem as co-residence selection.

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 estimate intergenerational earnings mobility using the two-sample two-stage least squares (TSTSLS) estimator.<sup>3</sup> 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 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.

When we want to study the intergenerational earnings mobility in the case of daughters, a second problem that arises 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. To give some intuitions of what happens in the case of daughters, we deal with this selection problem following Chadwick and Solon (2002) and using family incomes instead of daughter's individual earnings.

Why Spain? The literature on intergenerational earnings mobility has concentrated on 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. The studies of Mocetti (2007) and Piraino (2007) are two

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Nicoletti and Francesconi (2006) analyse intergenerational mobility using an occupational prestige score. They find that the  $\beta$  coefficient (where  $\beta$  represents the elasticity between father's and offspring's occupational prestige scores) is underestimated when they only consider the pairs of children and parent who are cohabiting.

<sup>3</sup>Following the paper written by Angrist and Krueger (1992) on two-sample instrumental variables (TSIV) estimation, numerous empirical researchers have applied a computationally convenient TSTSLS variant to the study of intergenerational mobility, like Björklund and Jäntti (1997) in Sweden; Fortin and Lefebvre (1998) in Canada; Grawe (2004) in Ecuador, Nepal, Pakistan, and Peru; Lefranc and Trannoy (2005) in France; Nicoletti and Ermisch (2007) in Britain; and by Mocetti (2007) in Italy.

exceptions, exploring intergenerational earnings mobility in Italy.

As in other southern European countries, Spain experiences stronger intergenerational family bonds compared to other countries outside the region. Indeed after leaving home, children maintain a close relationship with parents. Therefore, it is valuable to explore how earnings mobility in Spain compares to other countries, and it is particularly interesting to compare our results to those obtained by Mocetti (2007) and Piraino (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, Sanchez-Hugalde (2004) analyses the intergenerational income and education mobility in Spain 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. Another recent study about the intergenerational mobility in Spain is the paper of Güell, Mora, and Telmer (2007), in which they study the information contained in the surnames of the inhabitants of a large Spanish region as indicative of the degree of intergenerational mobility of an economy. The idea is that surnames capture family links in a manner that allows them to be used to extract longitudinal information from census data.

We find an elasticity around 0.40 for sons. When we analyse daughters following Chadwick and Solon (2002) approach we find nearly the same elasticities as for sons. 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 describe how we implement the two-sample two-stage least squares estimator. In Section 3 we describe the data source, the selection sample, and the variables used in the empirical analysis. In Section 4, we report the results, and finally, in Section 5, we offer some final remarks.

## 2 Estimation method

### 2.1 The econometric model

As we explained above, we focus on intergenerational mobility measured by the intergenerational elasticity of children's earnings (or income) with respect to paternal earnings (or income). More precisely, we consider the following intergenerational mobility equation:

$$W_{it} = \alpha + \beta W_{it-1} + \mu_{it} \quad (1)$$

where  $W_{it}$  is the children's log earnings (or our economic variable of permanent income),  $W_{it-1}$  is the fathers' log earnings (the economic variable of the previous generation),  $\alpha$  is the intercept term representing the average change in the child's log earnings, and  $\mu$  is a random error. The coefficient  $\beta$  is the intergenerational elasticity of children's earnings with respect to their father's earnings, and it is our parameter of interest.

Let  $\rho$  be the correlation between  $W_{it}$  and  $W_{it-1}$ ; then  $\beta$  is related to  $\rho$  by the following equation:

$$\beta = \rho \frac{\sigma_{W_{it}}}{\sigma_{W_{it-1}}} \quad (2)$$

where  $\sigma$  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  $\beta$  will be exactly equal to  $\rho$  when:  $\sigma_{W_{it-1}} = \sigma_{W_{it}}$ .

On the one hand, when  $\beta = 0$ , sons' 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 evaluate adequately 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 1 using the ordinary least squares 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  $\beta$ . 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  $\beta$ . 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 offspring around 40 years old.

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

## **2.2 Two sample two stage least squares estimator**

The estimation of intergenerational earnings mobility can frequently be biased due to different sample selection problems. One of the most important selection problems we experience in short panels is 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 who never co-reside with their parents during the panel. This selection problem could lead to a sub-estimation of the offspring's earnings, since living in the parental household is either because they are still students or they do not have enough income to live alone. 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 offspring's 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).

We deal with this selection problem linking two samples and using the TSTSLS estimator. We use one sample with information on adults and the characteristics (occupation, education, age) of the fathers when the sons are between 12 and 14 years old, and another sample with the same paternal characteristics, but also with their earnings.

The TSTSLS estimator is a computationally easier variant of two-sample instrumental variable estimator (2SIV) described by Angrist and Krueger (1992), Arellano and Meghir (1992), and Ridder and Moffit (2006).<sup>4</sup> Concretely, in the two-sample context, unlike the single-sample situation, the IV and 2SLS estimators are numerically distinct. Inoue and Solon (2010) derive and compare the asymptotic distributions of the two estimators and find that the commonly used TSTSLS estimator is more asymptotically efficient than the TSIV estimator because it implicitly corrects for differences in the distribution of variables between the two samples. Therefore, they explain that, although computationally simplicity was the original motive that drew applied researchers to use the TSTSLS estimator instead of the TSIV estimator, it turns out that the TSTSLS estimator also is theoretically superior.

Since we do not have information about  $W_{it-1}$ , but do have a set of instrumental variables  $Z$  of  $W_{it-1}$ , we can estimate equation (1) in two steps. As we have explained before, we consider two different 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 previous studies that estimate intergenerational mobility combining two different datasets, different variables have been used to impute the missing father's earnings.<sup>5</sup>

In the first step, we use the supplemental sample to estimate a log earnings equation

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<sup>4</sup>For a detailed description of the properties of this estimator, see Arellano and Meghir (1992), Angrist and Krueger (1992) and Ridder and Moffit (2006).

<sup>5</sup>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 (2005) instead use 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.



for fathers using, as explanatory variables, their characteristics,  $Z$ , that is:

$$W_{t-1} = Z_{t-1}\delta + v_i \quad (3)$$

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

$$\widehat{W}_{it-1} = Z_{it-1}\hat{\delta}, \quad (4)$$

where  $\hat{\delta}$  represents the coefficients estimated in the first step, and  $Z$  represents the variables observed in the main sample. Thus, we estimate equation 1 by using the fathers' imputed earnings.

$$W_{it} = \alpha + \beta(Z_{it-1}\hat{\delta}) + u_i \quad (5)$$

The  $\hat{\beta}$  we obtain is the TSTSLS estimate of intergenerational earnings elasticity. The standard errors are properly estimated as Murphy and Topel (1985) and Inoue and Solon (2010) propose. 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 properties of the two-sample estimator depend on the nature of the instrument used. Nicoletti and Ermisch (2007) express how important it is to choose instrumental variables that are strongly correlated with the variable to be instrumented. Therefore, we have to choose the instruments such that the  $R^2$  of the regression can be as high as possible.

Furthermore, consistency requires that the error term in the intergenerational mobility equation be independent of the instrumental variables or that the instrumental variables explain perfectly the father's missing earnings.

Therefore, the well-known rule for the choice of the instruments in the instrumental variable estimation based on a single sample applies to the TSTSLS estimation too. The instruments chosen should have the least correlation with the error in the main equation -the intergenerational mobility equation- and maximum multiple correlation with the variable to be instrumented -the fathers' earnings. Choosing instruments with minimum correlation with the error, but with low correlation with the fathers'

earnings (or, vice versa, with maximum correlation with the fathers' earnings, but high correlation with the error) does not cancel the potential bias.

As Nicoletti and Ermisch (2007) point out, the TSTOLS estimator of the intergenerational elasticity could be under- or overestimated when the auxiliary variables are endogenous. Moreover, since the instruments we use -paternal educational and occupational characteristics- are likely to be positively related to the sons' earnings even after controlling for fathers' earnings, the bias is probably positive. Therefore, the potential endogeneity problem is likely to affect most of the empirical papers on intergenerational mobility applying 2SIV and TSTOLS estimators. In order to measure the potential bias of the TSTOLS, we present in Appendix B the results of comparing the estimates using OLS and TSTOLS for the restricted sample of co-residing father-son pairs.

We also want to give some insight on the intergenerational earnings mobility for daughters. We deal with the selection problem mentioned in the introduction following Chadwick and Solon (2002) using family incomes instead of daughter's individual earnings.<sup>6</sup>

### 3 Data Sources and Sample Selection Rules

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).<sup>7</sup>

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

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<sup>6</sup>Chadwick and Solon (2002) use this approach to analyse the role of the assortative mating in the intergenerational economic mobility in the United States.

<sup>7</sup>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).

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 to estimate consumption and weigh 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 a homogenous classification across surveys.<sup>8</sup>

Our main sample is composed of children born between 1955 and 1975 who have information about father's characteristics. Thus, in 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 paternal 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 (and the fathers' income regression) we select males between those ages.

As noted 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 the closest measure of permanent earnings? Haider and Solon (2006) show that it is reasonable to choose children 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 sample of 3,520 son/father pairs and 3,995 daughter/father pairs. Table 1 and Table 2 present the principal descriptive statistics of our sample of sons and daughters respectively.

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<sup>8</sup>For a detailed description of the frequencies of the different characteristics in the main and supplemental samples see Table A.1 in Appendix A.

Table 1: Descriptive statistics: Characteristics of sons in the main sample

Variable	Mean	Standard deviation	Minimum	Maximum
Son's age in 2005	39.36	5.64	30	49
Son's log family income 2005	10.06	0.63	0.87	12.29
Father's age in 1981	45.84	5.08	37	57
Father's log earnings	13.2	0.36	12.34	14.11
Father's log income	13.24	0.33	12.46	14.13
Sample size	3520			

Table 2: Descriptive statistics: Characteristics of daughters in the main sample

Variable	Mean	Standard deviation	Minimum	Maximum
Daughter's age in 2005	39.55	5.66	30	49
Daughter's log family income 2005	10.02	0.66	4.09	12.05
Father's age in 1981	45.89	4.97	37	57
Father's log earnings	13.21	0.36	12.34	14.11
Father's log income	13.24	0.34	12.46	14.13
Sample size	3995			

## 4 Results

### 4.1 Intergenerational earnings mobility for sons

In order to compare our results with the empirical literature on intergenerational mobility, we present in this subsection our estimation of intergenerational earnings mobility for sons. We use a two-sample two-stage estimation, whose first step consists of the estimation of the paternal earnings regression using the supplemental sample, and the results of this regression are presented in Table 3. These coefficients are then used to impute the paternal 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, that is, the coefficients of the intergenerational regression between annual sons' earnings and the fathers' imputed earnings. In all columns, the father's predicted log earnings has a significant positive effect on child's earnings.

We estimate the elasticity for sons for different age ranges. The ranges considered are 30 to 40, 40 to 50, 30 to 50 (the whole sample) and a narrower range around 40 (those who are between 35 to 45). All the coefficients obtained are around 0.40 for all age specifications. We obtain a bit smaller elasticity for the younger sons. However

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)
<b>Education</b>	
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)
<b>Occupation</b>	
Upper-level manager	-0.4381 (0.0404)
Lower-level professional	-0.0753 (0.0986)
Routine upper-level non-manual employee	-0.0913 (0.0279)
Routine lower-level non-manual employee	-0.3158 (0.0320)
Skilled agriculture worker	-0.8155 (0.0306)
Skilled manual worker	-0.1395 (0.0300)
Lower-level technician	-0.2009 (0.0298)
Unskilled worker	-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**: Upper-level professionals (reference).

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

	Sons 30–40	Sons 40–50	Sons 30–50	Sons 35–45
Father’s earnings	<b>0.38</b> (0.042)	<b>0.43</b> (0.042)	<b>0.40</b> (0.029)	<b>0.41</b> (0.041)
Age	0.14 (0.004)	0.02 (0.004)	0.02 (0.002)	0.02 (0.004)
Constant	4.26 (0.597)	3.32 (0.603)	3.89 (0.413)	3.21 (0.585)
Obs.	1334	1322	2656	1501
$R^2$	0.061	0.08	0.08	0.08

Note: The dependant variable is the log of annual labor earnings. Father’s earnings refers to the log of father’s annual labor earnings. Standard errors are corrected using Murphy and Topel (1985) and Inoue and Solon (2010) procedure.

we do not have enough information to know if it is due to a change in the trend such that we will have more mobility or if it is only a matter of age in the sense that when these young sons grow older they would become more correlated with their parents.

Once we have estimated our beta for sons is not immediate if the figure we get means high or low mobility. We can use the figures reported in other studies to compare. However, the comparability of studies is problematic and very difficult since the estimates are sensitive to different factors such as the income measure used, the adequacy of the database, the different criteria for sample selection and the different estimation methods followed. Therefore, so as to compare our results with those of other studies, we must be careful and choose the studies that are most similar to ours in terms of choice of the sample, using two-sample approach.<sup>9</sup>

Fortunately, at present there are some studies that appear very close to our analysis because they use similar methodologies and sample selection rules, allowing us to make an international comparison. 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 and they obtain elasticities that ranges from 0.20 to 0.25 for sons. In the same way, Lefranc and Trannoy (2005) for France, find an elasticity of 0.40 for sons. Furthermore, Mocetti (2007) show Italy as a very immobile society. In particular, he finds elasticities around 0.50.

As Lefranc and Trannoy (2005) 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

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<sup>9</sup> 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.

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.

Tables A.2 and A.3 in Appendix A show the transition matrices for earnings and education between fathers and sons. These tables give us an intuitive vision of the persistence of earnings or education. Both tables show a strong degree of persistence. If we consider the persistence of education as one of the mechanisms that enhances the persistence of earnings, the design of education policies should take this into account to increase mobility.

## 4.2 Intergenerational earnings and income mobility for daughters

As explained above, the empirical literature on intergenerational earnings mobility has concentrated on the analysis of sons to avoid the employment selection problem. 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).

However, in this subsection we want to give some insight into the intergenerational earnings mobility for daughters. We deal with this selection problem following Chadwick and Solon (2002) and using family incomes instead of daughter's individual earnings.<sup>10</sup>

In Table 5 we reproduce the Chadwick and Solon (2002) approach and we estimate the elasticity between daughters (using different dependent variables) and fathers earnings. In order to compare these results, we also do the same exercise for sons in Table 6.

In the first row of Table 5 and Table 6, we consider the log of family income as

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<sup>10</sup>Chadwick and Solon (2002) use this approach to analyse the role of the assortative mating in the intergenerational economic mobility in the United States.

Table 5: Intergenerational elasticity for daughters respect to their father’s earnings

Dependent variable	Full daughters sample	Married daughters
Log family income	<b>0.386</b> (0.028)	<b>0.384</b> (0.033)
Log couple’s earnings		<b>0.497</b> (0.044)
Sample size	3995	1904

Note:Standard errors are corrected using Murphy and Topel (1985) and Inoue and Solon (2010) procedure.

Table 6: Intergenerational elasticity for sons respect to their father’s earnings

Dependent variable	Full sons sample	Married sons
Log family income	<b>0.404</b> (0.027)	<b>0.388</b> (0.032)
Log couple’s earnings		<b>0.565</b> (0.042)
Sample size	3520	1940

Note:Standard errors are corrected using Murphy and Topel (1985) and Inoue and Solon (2010) procedure.

a dependent variable. In the second row, we restrict the sample to those who are married and we consider the log of the couple’s combined earnings.

Concretely, we present the results of the estimation of equation 5 by the TSTOLS estimator with different dependent variables and samples. We begin (in the first row, first column of Table 5) with the estimation of the elasticity of daughter’s family income with respect to her father’s earnings for our full sample of 3995 daughters and we obtain an elasticity of 0.38. As we can see in Table 6, for the full sample of 3520 sons, we find an elasticity of 0.40. Therefore, the elasticities between daughter’s and father’s earnings are very little smaller than the sons’ elasticity, however not statistically different.<sup>11</sup>

When we do the same, but considering only daughters who are married (first row, second column) with respect to paternal earnings in Table 5, we obtain a very similar elasticity of 0.384.<sup>12</sup> For sons we estimate an elasticity of 0.388. Again, the results

<sup>11</sup>The t-ratio for the contrasts between these two coefficient is 0.46, so the contrast is not statistically significant at conventional significance levels.

<sup>12</sup>We consider married daughters those who are legally married and those who live in couple.



obtained are very similar by genders.

For married daughters and sons we also analyse the paper of couple's earnings. Therefore, in the second row of each table we estimate the elasticity between couple earnings (the log of the sum of the daughter's earnings and her husband's earnings) and paternal earnings. In this case the elasticities increase to 0.50 for married daughters and 0.57 married sons. The figure 0.57 may seem relatively high compared to 0.50, and higher mobility for daughters is also found in Chadwick and Solon (2002) and Ermisch, Francesconi, and Siedler (2006), but the t-ratio of 1.12 again did not allow us to reject the null hypothesis of equal coefficients.

In Table A.4 and Table A.5 in Appendix A, we present the same exercise using paternal income as an explanatory variable. Again we obtain results in the same direction.

## 5 Final remarks

In this paper, we contribute to the empirical literature that calculate the intergenerational mobility for different countries estimating the earnings and income elasticity for Spain. Using the two-sample two-stage least squares estimator, we find sons' elasticities around 0.40. Using Chadwick and Solon (2002) approach and comparing the estimates for sons and daughters, our results suggest that elasticities for both genders are nearly the same.

Where does Spain fit into the larger picture of intergenerational mobility? In some ways, it's in the middle. It is similar to France, lower than the Nordic countries and Britain, and higher than the United States. Compared to other developed countries, Spain is relatively immobile, but it is more mobile than Italy, the only other southern European country for which we have evidence.

# Appendix A

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

	supplemental sample	main sample
Observation	5,032	4,352
<b>Education</b>		
Did not 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
<b>Occupation</b>		
Upper-level professional	9.25	8.04
Upper-level manager	4.28	3.70
Lower-level professional	3.43	5.58
Regular upper-level non-manual employee	11.04	6.18
Regular lower-level non-manual employees	9.85	7.25
Skilled agriculture worker	12.74	12.85
Skilled manual worker	15.88	24.99
Lower-level technician	13.81	11.82
Unskilled worker	19.71	19.60

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

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

		Father's quantile				
		1	2	3	4	5
Quantile 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 children

		Father's education					
		0	1	2	3	4	5
Child's education	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%

Table A.4: Intergenerational elasticity for daughters with respect to their father's income

Dependent variable	Full daughters sample	Married daughters
Log family income	<b>0.435</b> (0.030)	<b>0.435</b> (0.036)
Log couple's earnings		<b>0.561</b> (0.048)
Sample size	3995	1904

Table A.5: Estimated intergenerational elasticity for sons and daughters with respect to their father's **income**

Dependent variable	Full sons sample	Married sons
Log family income	<b>0.461</b> (0.030)	<b>0.455</b> (0.034)
Log couple's earnings		<b>0.653</b> (0.046)
Sample size	3520	1940

## Appendix B

As we explain in Section 2.2, the TSTSLS estimation could produce an overestimation of  $\beta$  when the variables used to impute father earnings are endogenous and do not perfectly explain father earnings. In order to measure the potential bias of the TSTSLS, we can use the restricted sample of father-son pairs who co-reside and compare the estimates using OLS and TSTSLS.

The estimation results are reported in Table B.1

Table B.1: Intergenerational earnings elasticity for father-son pairs who co-reside

	Sons 30–40	Sons 40–50	Sons 30–50	Sons 35–45
TSTSLS	0.21 (0.022)	0.273 (0.021)	0.23 (0.018)	0.24 (0.014)
OLS	0.20 (0.025)	0.25 (0.025)	0.22 (0.012)	0.21 (0.016)

Note: The dependant variable is the log of annual labor earnings. Father's earnings refers to the log of father's annual labor earnings. Standard errors are corrected using Murphy and Topel (1985) and Inoue and Solon (2010) procedure.

We do not find evidence of a large amount of upward bias. This results are in line with Nicoletti and Ermisch (2007) and Aaronson and Mazumder (2008).

## References

- AARONSON, D., AND B. MAZUMDER (2008): “Intergenerational economic mobility in the United States, 1940 to 2000,” *Journal of Human Resources*, 43(1).
- ANGRIST, J. D., AND A. B. KRUEGER (1992): “The effect of age at school entry on educational attainment: an application of instrumental variables with moments from two samples,” *Journal of the American Statistical Association*, 87, 328–336.
- ARELLANO, M., AND C. MEGHIR (1992): “Female labour supply and on-the-job search: an empirical model estimated using complementary data set,” *The Review of Economic Studies*, 59, 537–559.
- BEHRMAN, J. R., AND P. TAUBMAN (1990): “The intergenerational correlation between children’s adult earnings and their parents’ income: results from the Michigan Panel Survey of Income Dynamic,” *Review of Income and Wealth*, 36(2), 115–127.
- BJÖRKLUND, A., AND M. JÄNTTI (1997): “Intergenerational income mobility in Sweden compared to the United State,” *American Economic Review*, 87, 1009–1018.
- (2000): “Intergenerational mobility of socioeconomic status in comparative perspective,” *Nordic Journal of Political Economy*, 26(1), 3–32.
- BOWLES, S., AND H. GINTIS (2002): “The inheritance of inequality,” *Journal of Economic Perspectives*, 16, 3–30.
- CARABAÑA, J. (1999): *Dos estudios sobre movilidad intergeneracional*. Fundación Argendaria-Visor (ed.).
- CHADWICK, L., AND G. SOLON (2002): “Intergenerational income mobility among daughters,” *American Economic Review*, 92(1), 335–344.
- CORAK, M., AND A. HEISZ (1999): “The intergenerational earnings and income mobility of canadian men: evidence from longitudinal income tax data,” *Journal of Human Resources*, 34(3), 504–533.
- COUCH, K., AND T. DUNN (1997): “Intergenerational correlations in labor market status: a comparison of the United State and Germany,” *Journal of Human Resources*, 32(1), 210–232.
- ERIKSON, R., AND J. H. GOLDTHORPE (2002): “Intergenerational inequality: a sociological perspective,” *Journal of Economic Perspective*, 16, 31–44.
- ERMISCH, J., M. FRANCESCONI, AND T. SIEDLER (2006): “Intergenerational economic mobility and assortative mating,” *Economic Journal*, 116, 659–679.
- FORTIN, N., AND S. LEFEBVRE (1998): “Intergenerational income mobility in Canada,” in *Labour Market, Social Institution and the Future of Canada’s Children*, ed. by M. Corak. Statistics of Canada, Ottawa.
- GRAWE, N. (2004): “Intergenerational mobility for whom? The experience of high- and low-earnings sons in intergenerational perspective,” in *Generational Income Mobility in North America and Europe*, ed. by M. Corak. Cambridge University Press, Cambridge.
- GÜELL, M., J. V. R. MORA, AND C. TELMER (2007): “Intergenerational mobility and the informative content of surnames,” Economics Working Papers 1042, Department of Economics and Business, Universitat Pompeu Fabra.

- HAIDER, S., AND G. SOLON (2006): “Life-cycle variation in the association between current and lifetime earnings,” *American Economic Review*, 96(4), 1308–1320.
- INOUE, A., AND G. SOLON (2010): “Two-sample instrumental variables estimators,” *The Review of Economics and Statistics*, 92(3), 557–561.
- LEFRANC, A., AND A. TRANNOY (2005): “Intergenerational earnings mobility in France: Is France more mobile than the U.S.?” *Annales d’Economie et de Statistique*, (78), 03.
- MOCETTI, S. (2007): “Intergenerational Earnings Mobility in Italy,” *The B.E. Journal of Economic Analysis & Policy*, 7: Iss. 2 (Contributions), Article 5.
- MURPHY, K. M., AND R. H. TOPEL (1985): “Estimation and inference in two-step econometric models,” *Journal of Business & Economic Statistics*, 3(4), 370–79.
- NICOLETTI, C., AND J. ERMISCH (2007): “Intergenerational earnings mobility: changes across cohorts in Britain,” *The B.E. Journal of Economic Analysis and Policy. Contributions*, 7: Iss. 2 (Contributions), Article 9.
- NICOLETTI, C., AND M. FRANCESCONI (2006): “Intergenerational mobility and sample selection in short panels,” *Journal of Applied Econometrics*, 21(8), 1265–1293.
- ÖSTERBACKA, E. (2001): “Family background and economic status in Finland,” *Scandinavian Journal of Economics*, 103(3), 467–484.
- PIRAINO, P. (2007): “Comparable Estimates of Intergenerational Income Mobility in Italy,” *The B.E. Journal of Economic Analysis & Policy*, 7: Iss. 2 (Contributions), Article 1.
- RIDDER, G., AND R. MOFFIT (2006): “The econometrics of data combination,” in *Handbook of Econometrics*, ed. by Heckman, and Learner, 6. Elsevier Science, North Holland, Amsterdam.
- SANCHEZ-HUGALDE, A. (2004): “Movilidad intergeneracional de ingresos y educativa en España (1980-90),” Discussion paper.
- SOLON, G. (1992): “Intergenerational income mobility in the United States,” *American Economic Review*, 82(3), 393–408.
- (1999): “Intergenerational mobility in the labour market,” in *Handbook of Labor Economics*, ed. by O. Ashenfelder, and D. Card, vol. 3, chap. 29, pp. 1761–1800. Amsterdam: Elsevier.
- (2002): “Cross-country differences in intergenerational earnings mobility,” *Journal of Economic Perspective*, 16(3), 59–66.
- ZIMMERMAN, D. (1992): “Regression toward mediocrity in economic stature,” *American Economic Review*, 82, 409–429.