How important is the assortative mating to understand the intergenerational mobility in Spain?

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Very preliminary version. Please don't quote.

Abstract

This paper analyses the role played by assortative mating to understand the intergenerational economic mobility in Spain. Since there are no Spanish surveys covering long-term information on both children and their fathers' earnings, we deal with this selection problem using the two-sample two-stage least squares estimator.

We find that assortative mating plays an important role in the intergenerational transmission process. Among married offspring, spouse's earnings appear to be just as elastic as the offspring's own earnings with respect to the parents' income.

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

JEL classification: D31, J31, J62.

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1 Introduction

The empirical literature on intergenerational mobility have been mainly concentrated in the correlation in somewhat socieconomic variable between son and his father. More rarely, the correlation between fathers and daughters. However, those sons and daughters usually becomes someones's spouse, and the way in which this matching occurs may have consequences for their own socio-economic position. The offspring status not only is correlated with their parents status, also it is correlated with their parents-in-law position.

In this paper I estimate the extent to which assortative mating affects intergenerational economic mobility in Spain.[1] We find that assortative mating is an important element to understand the intergenerational mobility across generations.

There is a lot of evidence of high correlation in the characteristics between husband and wives. For example, Epstein and Guttman (1984) document positive correlations between spouses with respect to age, physical size, intelligence test scores, religion, ethnicity, and certain values and personality traits. Economist has focused on educational attainment and earnings. For example, Kremer (1997) finds that the spouse correlation in years of schooling in the United State is a little above 0.6. Kalmijn (1994) points out two hypothesis of why this correlation occurs. In the cultural matching hypothesis people prefer to marry someone of similar cultural status. On the other hand, in the economic competition hypothesis people prefer to marry someone of high economic status. At the end both theories generate assortative mating.

Furhtermore, marriage can be consider one of the most important institution through which economic mobility and social stratification took place (Ermisch, Francesconi, and Siedler (2006)).

There are some studies that analyses the link between assortative mating and intergenerational mobility. All find that assortative mating is an important element in the intergenerational transmission process. Lam (1995), analysing the case of Brazil, obtain a greater effect of father-in-law schooling than father's schooling on the wage of

[1]We refers to assortative mating as the tendency of men and women with similar socioeconomic characteristics to marry. Matching generally takes place in some private and professional environments. This fact generate that people with similar characteristics mates.Therefore partnership is not a random process.

male workers and they interpret this result as evidence of a high degree of assortative mating in the marriage market.

More recently, we have the study of Chadwick and Solon (2002) that analyses the case of United State. They find that assortative mating play an important key role in the intergenerational transmission in the United State. They shows that the individual earnings of husbands and wives are equally highly correlated with the incomes of their own parents as they are with respect to the incomes of the parents-in-law. The correlation of earnings among married couples is somewhat higher with respect husband's parents earnings than with respect to wife's parents.

Ermisch, Francesconi, and Siedler (2006), analysing the case of Germany and Great Britain, show that assortative mating is also important in explaining intergenerational earnings persistence. They refer to three institutions that produce differences in intergenerational mobility and assortative mating between countries. The first one, could be the educational system. Education play an important role in the intergenerational transmission of earnings or income. Furthermore, also education may directly affect assortative mating. Second, country's labour market institution affect the return tho human capital investment and gender differences in it, and this in turn affect intergenerational mobility. Third, families differ in the weight given to the next generation's income prospects in their decisions, and there could be differences in the average weight between countries.

In a recent paper, Raaum, Bratsberg, Red, sterbacka, Eriksson, Jntti, and Naylor (2007), present comparable evidence from several countries on intergenerational earnings mobility with a focus on mobility among women. They explain how assortative mating and family labour supply decisions are important determinants of the intergenerational persistence of earnings.

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 offsprings' and parents' economic varibles 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. This selection problem is particularly important in Spain, where we have only short panels, and thus, do not have information on both children's and their fathers' permanent earnings.[2] 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 mobility using the two-sample two-stage least squares estimator (TSTSLS).[3] This method combines information from two separate samples: a sample of adults (sons and daughters) with observations of their earnings and their parents' characteristics, and a sample of potential parents with observations on earnings and the same characteristics. The latter sample is used to estimate an earnings equation for parents using their characteristics as explanatory variables, while the former is used to estimate an intergenerational earnings equation by replacing the missing parents' earnings with its best linear prediction

The rest of the paper is organised as follows. In the next section, we describe how we implement the two-sample two-stage least square 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

To analyse the role played by the asortative mating in the intergenerational mobility we focus on intergenerational mobility measured by the intergenerational elasticity of children's earnings (or income) with respect to father's or father-in-law's earnings (or income). More precisely, we consider the following intergenerational mobility equation:

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

[2]Nicoletti and Francesconi (2006) refer to this sample selection problem as co-residence selection.

[3]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, such as 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.

where W_{it} is the children's economic variable of permanent income (income or earnings), W_{it-1} would be the fathers' or fathers'-in-law economic variable of permanent income (the variable 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. The coefficient β is the intergenerational elasticity of children's earnings with respect to their fathers' or fathers-in-law earnings, and it is our parameter of interest.

When $\beta = 0$, sons' earnings are not determined by their previous generation. On the other hand, a value of $\beta = 1$ represents a situation of complete immobility; that is, children's earnings are fully determined by the previous generation. Generally, the coefficient is between these two values.

If we had permanent income for successive generations in our sample, we would directly estimate equation 1 using the ordinary least square estimator without any problem. Unfortunately, we do not have this information in one data set.

First, most data sets only provide measures of current earnings and fail to provide measures of individual permanent income. Solon (1992) and Zimmerman (1992) show that the use of current earnings as a proxy for permanent earnings leads to downward OLS estimates of β. Different solutions can be implemented to reduce or eliminate this bias. If we work with panel data, we can calculate an average of current earnings over several years as a proxy of permanent income. Another possibility lies in using instrumental variables to estimate β. In this paper, in the case of the father's or father-in-law's earnings or income, 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 or father-in-law'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) suggest the use of offsprings around 40 years old.

Second, 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 offsprings' 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 offsprings' earnings).

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

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).[4] 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.[5]

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

[5] 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,

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:

$$W_{t-1} = Z_{t-1}\delta + v_i \tag{2}$$

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,

$$\widehat{W_{it-1}} = Z_{it-1}\hat{\delta}, \tag{3}$$

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.

$$W_{it} = \alpha + \beta(Z_{it-1}\hat{\delta}) + u_i \tag{4}$$

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, to obtain consistent estimators, 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.

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.

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 TSTSLS 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 TSTSLS estimators.

3 Data set and sample selection

As we explained above, we combine two separate samples to analyse the role of the assortative mating on the 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).[6]

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

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

Our supplemental sample is the Family Expenditure Survey of 1980-1981 (Encuesta

[6]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).

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

Although we have the same characteristics in both samples, we have to recode some variables to have an homogenous classification across surveys.[7]

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

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

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

After the exclusions, we have a sample of 3,520 son/father pairs and 3,995 daughter/father pairs.

Tables 1 and 2 present the principal descriptive statistics of our final sample of

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

daughters and sons, respectively.

Table 1: Descriptive statistics: Characteristics of Daughters in the main sample.

Variable	**Mean**	**Standar 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 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			

Table 2: Descriptive statistics: Characteristics of Sons in the main sample.

Variable	**Mean**	**Standar 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 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			

4 Results

In this section we present the results of the estimation of equation (4) by TSTSLS estimator with different dependent variables and samples. As we have explained before, the first step of the TSTSLS estimation consists of the estimation of the fathers' earnings regression using the supplemental sample. The results of this regression are presented in the Appendix (Table A.2). These coefficients are then used to impute the fathers' earnings in the main sample, since we have the same characteristics in both samples (main and supplemental). Therefore, in the second step, using the coefficients from the supplemental sample and the characteristics of the main sample, we estimate earnings for each father in the main sample.

In Table 3 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 4.

We begin (in the first row, first column of table 3) 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. We use the daughter's

Table 3: Intergenerational elasticity for daughters respect to their father's earnings

Dependent variable	**Full Daughters sample**	**Married Daughters**	**Married daughters whose husband have positive earnings**
Log family income	**0.386**	**0.384**	**0.384**
	0.028	0.033	0.033
Log of couple's combined earnings		**0.497**	**0.497**
		0.044	0.044
Log of husband's earnings			**0.395**
			0.039
Log of husband's share of combined earnings			**-0.01**
			0.002
Sample size	**3995**	**1904**	**1901**

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

family income 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).

In Table 4 we present the same elasticity for sons. For the full sample of 3520 sons we estimate an elasticity of 0.40. The elasticities between daughter's and father's earnings are very little smaller than the sons' elasticity, however not statistically different.[8]

One of the main objective of our paper it to analyse the role of assortative mating in intergenerational mobility of married daughters. Therefore, we do the same, but considering only daughters who are married (first row, second column) with respect to paternal earnings in table 3 and we obtain a very similar elasticity of 0.384.[9] For sons we estimate an elasticity of 0.388. Again, the results obtained are very similar by genders.

For married daughters and sons we also analyse the role of couple's earnings. There-

[8]The t-ratio for the contrasts between these two coefficient is 0.46, so the contrast is not statistically significant at conventional significance levels.

[9]We consider married daughters those who are legally married and those who live in couple.

Table 4: Intergenerational elasticity for sons respect to their father's earnings

Dependent variable	**Full sons sample**	**Married Sons**	**Married sons with positive earnings**
Log family income	**0.404**	**0.388**	**0.388**
	0.027	0.032	0.032
Log of couple's combined earnings		**0.565**	**0.565**
		0.042	0.042
Log of son's earnings			**0.474**
			0.037
Log of son's share of combined earnings			**-0.007**
			0.002
Sample size	**3520**	**1940**	**1937**

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

fore, 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. 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 order to deepen the role played by assortative mating, in the third row we use as dependent varible the log of husband's earnings. We obtain an elasticity of 0.39 a little lower than the couple's elasticity but not statistically significant. The fourth row of the table shows the estimated elasticity of the daughter's husband's share of their combined earnings with respect to the fathers' earnings. The coefficient of -0.01 is insignificantly different from zero and this results suggest that elasticities of the daughter's earnings and her husband's earnings with respect to her fathers' earnings are nearly the same.

In tables A.3 and A.4 in Appendix A, we present the same exercise using paternal income as an explanatory variable. Again we observe the same pattern.

5 Final remarks

In this paper, we contribute to the empirical literature that try to know the role play by the assortative mating in the intergenerational mobility. Using the two-sample two-stage least square estimator, we find that elasticities between daughter's and father's earnings are very little smaller than the sons' elasticity, however not statistically different.

We also find that assortative mating plays an important role in the intergenerational transmission process. Among married offspring, spouse's earnings appear to be just as elastic as the offspring's own earnings with respect to the parents' income.

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
Education		
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
Occupation		
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: 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).

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Table A.3: Intergenerational elasticity for daughters with respect to their father's income

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

Table A.4: Estimated intergenerational elasticity for sons and daughters with respect to their father's income

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

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