Direct and Indirect Effects of Parental Background in Spain: The role of quality of Education, Human Capital & Social Networks

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Abstract

This thesis takes an insight look at the situation of inter-generational mobility and parental background effects in Spain. Taking advantage of a new data base, we are able to deepen the previous analysis considering individual characteristics affected by parents like, education, type of school attended, human capital promotion by parents, occupation and social network effects on their education attainment, occupational outcome and earnings of individuals and the household level. These results are consistent with literature proving the existence of imperfect labor markets and a slight unequal educational quality.

Keywords: inter-generational mobility, educational economics, labour economics, parental background

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1 Introduction

Looking at today's economic and social situation we find lots of social unrest and political conflict, mostly related to the fact of a feeling of unfair opportunities in terms of education or occupational outcomes, that result in different salaries and living conditions. Those unfair differences are mostly captured by parental backgrounds. Such differences are noticeable in the fact of being able to attend to private schools that allows for a better quality of education, peer influence and social networks (Green, Machin, Murphy, and Zhu, 2012),(Mancebón and Muñiz, 2008), (Cordero, Prior, and Simancas, 2016)). Moreover, there exist the perception that access or success in the labor market is also influenced by their background. Checchi, Ichino, and Rustichini (1999) shows that despite having a lower inequality of education attainment there is less mobility in Italy compared to the US because of labor market imperfections. In this case, Spain shows many similarities with Italy, in terms of background premiums and inter-generational mobility (Raitano and Vona, 2015a).
Taking all this into account, it is worth mentioning that there has been a well documented rise in income inequality levels among developed countries since the 70's Birdsall (2006), Castells-Quintana, Ramos, and Royuela (2015) and Spain is not the exception. This rise in income inequality can harm social well being in many different ways, one of the consequences that arises from the rise in inequality is the mistrust in political institutions as the detachment of individuals towards institutions results in lower turnouts and a bias of political parties towards the well-off given their higher participation rate Schäfer (2012). Thus, we have seen the rise of populist movements on both sides of the political spectrum that put the burden of the recent periods of economic crisis (Great Recession, Covid-19 pandemic, Ukrainian War..) on different social groups (the elites, immigrants, the status quo...). The question then is how does inequality relate to inter-generational mobility and this is related through the Great Gatsby curve, where countries with higher inequality tend to be less mobile. Although there exist many theories on their persistence such as human capital investment, credit constraints, social influences and power differentials in voting that result in certain policies among others as shown by Durlauf, Kourtellos, and Tan (2022) explaining the Gatsby curve. We will focus in the role played by the background of individuals to see their channels of transmission. As mentioned before, Checchi, Ichino, and Rustichini (1999) showed how even though the US was having higher inequality levels than Italy, the US was more mobile. Those findings suggest that looking just at income inequality is not enough, thus it is necessary to look at the broader picture for instance, considering the educational system or social networks which may play a significant role in the determination of their individual performance.

In this respect this thesis contribute to the literature of inter-generational mobility in addressing which are the direct effects (those of parental background on occupation and earnings) and indirect effects (those acting through education and other channels) focusing not only on the amount of education but also on the type of education given the new data set. With this analysis we improve the previous literature on RBC (Residual Background Correlations) where the effects of both, quality of education and the effect of social networks remained in the error term. In other words in this thesis, we will be able to better disentangle the mechanisms through which parental background is affecting education, occupation and earnings of children. Thus, being able to look on the fairness or unfairness of the Spanish social and economical distributions.

In recent years, there has been an shift both the academia and the public debate from inequality towards inequality of opportunities, in research and also in the public debate ((Chetty, 2021), (Chetty, Hendren, Kline, and Saez, 2014a), (Chetty, Hendren, Kline, Saez, and Turner, 2014b)). More recent studies (e.g. Marrero and Rodríguez (2013), Checchi and Peragine (2010)) have put the focus on Inequality of Opportunities (IO) and its relationship with growth. The idea is that total inequality can be decomposed between individual characteristics that are out of its control (gender, race, parental background, neighbourhood at child...), and differences in effort (under individual control) or somehow randomly distributed (ability). The first group results to be growth deterring while the second group results to be growth enhancing. Logically those differences due to ability or effort should be incentiviced from the labor market perspective as they reflect personal choices, on the contrary those differences where the individual has no choice, results in an inefficient resource allocation, thus diminishing potential economic growth.

In that sense, we find that parental background effects (for top income parents) exist in Spain and are even present when controlling for a set of tested transmission channels, suggesting, that education and occupation are the main drivers of such inter-generational transmission of inequalities. Also, we show that human capital transmission has a positive effect on both education and occupation and, thus, on earnings. Two other insights that we can learn from our study is that the type of school attended matters, not that much for educational success but for labor market performance. Our interpretations is that the social networks exert as an insurance effect that help individuals to avoid unemployment at the expense of lower wages.

When looking at the regional differences it out stands that Madrid is by far the only region where both middle income and top income parents exert a positive effect on their children's earnings. On the other hand we have North Eastern region where middle income parents have a negative effect on their children's earnings when comparing it to the children of low income parents.

Finally, this thesis contributes with two different strands of the literature. First, extending the previous empirical evidence of the the existence on effects of parental background on child's education, occupation and earnings in Spain. Documenting the strong influence on parental background in educational performance and dropout rates, showing a strong correlation of occupation (sectorial and even company wise) showing the wage premiums obtained by children who follow such traits. See for instance, (Cervini-Plá, 2015), (San-Segundo and Valiente, 2003), (De Pablos Escobar and Gil Izquierdo, 2016), (Martín and Garcia-Perez, 2022).
Second, our paper also introduces a novelty analysis for the case of Spain, where we take into account other channels through which background characteristics influence earnings, education & occupation. In this matter we also take into account Human Capital promotion by parents, quality of education (type of school attended) and effects of social networks in labor market access. And that this behavior has had an impact on the outcomes both in education and occupation in different levels. Chetty, Friedman, Saez, Turner, and Yagan (2020) proved that a large part of inter-generational income inequality is transmitted because of the different access to certain universities that face students from different parental background.

1.1 The Spanish Case

Gil-Hernández, Marqués-Perales, and Fachelli (2017) provided the bigger picture of the Spanish case by covering a large period from the 50's until 2011, and where they suggest that the increase in income fluidity across generations is due to the increase in the educational system and that parental background premiums have remained more or less equal. Quite interesting is the approach taken by Güell, Rodríguez Mora, and Telmer (2007), where it demonstrated that there is a correlation between income and surnames in Catalonia, meaning that such family cluster may influence labor market outcomes of their relatives. Moreover it also accounts that the decrease in mobility has been also being affected by an increase in assortative mating.
Later, many papers have used the EU-SILC module on inter-generational transmission of disadvantages of 2005 and 2011 for their analysis Pascual (2009), shows the linkage between status of the parents and earnings of the children, although she considers education in Spain as an homogeneous treatment given the major public financiation, issue that we will discuss in our paper. De Pablos Escobar and Gil Izquierdo (2016) makes us understand that even though educational mobility has increased, occupational mobility continues to be rigid. A re-

duction in mobility in recent years has also been noticed by Martín and Garcia-Perez (2022), Suárez Álvarez and López Menéndez (2018).

The rest of the thesis is organized as follows. Section 2 we present the data, description of the main variables, our sample selection and some descriptive analysis. The methodology is explained in section 3. The results appear in section 4 and finally, in section 5, we present the main conclusions.

2 Data and Methodology

2.1 Data and sample selection

We will be using the database carried out by the *Centro de Investigaciones Sociologicas* (CIS) on their module on "Social Inequality and Social Mobility in Spain". The database used in this paper is new and unique for Spain. It is representative of the Spanish population of 2017, containing a total of 2484 valid interviews.

The survey contains information on three different types of variables. The first one, a set of common variables of any CIS survey (age, family structure, place of residence...). Secondly, the outcomes at the individual and household level (net income, highest level of education, occupation, health...). Finally, the set of variables that define the background of the individuals (neighbourhood, family preferences, education type...) those variables are recorded in a retrospective way, meaning that such information comes from the idea of the interviewed person when they were 16 years old. When comparing our data set to the EU-SILC which is the main database used in such studies, we see that ours has smaller number of observations but in contrast contains a richer set of individual characteristics regarding their childhood. That, enable us to properly estimate and conduct the analysis of direct and indirect effect of parental background with more precision than in other studies, and also to understand which are the ways of transmission of inequalities.[1]

In line with other literature on Inter-generational Mobility(literature on sample selection in mobility) we have restrained our analysis to individuals aged between 25 and 60 years old to avoid any life-cycle bias in income (Böhlmark and Lindquist, 2006), leaving out data set with a total amount of 1543 observations.

[1]The EU-SILC is the European Union survey on income and living conditions, with the module on Intergenerational Transmission of Disadvantages.

2.2 Methodology

The first thing we did is to take the household size and apply the modified OECD equivalence scale proposed by Hagenaars, De Vos, Asghar Zaidi et al. (1994), where the first adult as a weight of 1, following adults in the household would take a weight of 0.5 as well as youngsters above 15 years old, those under 15 years old have a weight of 0.3. Then, we do have data on household total income [2] in brackets [3] we have transformed this variable into a continuous variable by applying a randomization of the actual value of the brackets. To obtain our outcome variable, the adjusted household monthly income, we divide total household income by the household equivalent scale. Then, categorize the background of the parents, given that we do not posses the actual income of the parents we can not compute the inter-generational income elasticities. To solve for this issue, we have used the ISCO occupational codes of the parents, choosing the highest of both parents as opposed to previous literature Erikson, Goldthorpe, Goldthorpe et al. (1992) given the increasing role of mothers in the labor market, although for such households where the mother was inactive, we have taken the occupation of the father as their background and we have dropped all observations for which it was impossible to obtain their background.[4]

To construct the *Human Capital* variable, we have used two variables. The first one, being *Cultural activities promotion* ranging from the lowest value 1 to the highest value 4, and adding the variable *Expenditure on their education* either being time or financial resources, ranging from the lowest value 1 to the highest value 4[5]. Thus by adding both variables we have a more or less continuous variable from 1 to 8.

Following Raitano and Vona (2015a), the main feature of our analysis is to understand the direct influence of family background on other outcomes (education and occupation), as well as the indirect effects acting through education. To understand such framework we have derived a wage equation for the household with background i with a level of education e and an occupation o, finally an innovation will be to account for human capital transmission

[2]notice that we have used household data for the purpose that we have more observations than for individual income (although the same regressions and procedure will be done in the Appendix 10). Also we were having a total of 500 missing observations of household income thus, we have estimated the household income 4 for the ones missing given all information that we had available to increase the amount of observations that we had

[3]from 0 to 300. Then from 301 to 600, from 601 to 900, from 901 to 1200, from 1201 to 1800, from 1801 to 2400, from 2401 to 3000, from 3001 to 4500, from 4501 to 6000 and finally more than 6000

[4]The lowest occupational group, it is composed by ISCO categories from 6-9, the medium category it is composed by groups 3-5 and the top category of parental background is composed by ISCO categories from 1-2.

[5]The initial variable had values from 1 to 10 but we have reduce it to 4, by dividing the initial value by 2.5 to have the same scale as *Cultural activities promotion*

channels through a series of variables that we have transformed to build an index of Human Capital [6] HC, the social network influence through sn that contains information on social network influence on current job acquisition and X that will be our set of control variables[7]:

$$ln(\mathrm{w}_{ieoh}) = \beta_0 + \beta i Background + \beta_e f(e|i) + \beta_o f(o|e,i) + \beta_h HC_i + \beta_s SN_i \rho *' X_i + \epsilon_i \quad (1)$$

Where w_{ieo} is the household adjusted salary for each household with background i given education e with occupation o and human capital h. $f(e|i)$ is the educational attainment as a function of background; $f(o|ei)$ is the occupation status given its education and background, h captures the human capital transmission channel and s the social network effect. Then β_e, β_o and β_h β_s are the returns to education, occupation and transmitted human capital respectively, being ϵ_i the error term. Our interest coefficient is β_i that captures the effect of parental background. To sum up, in our analysis we are capturing most of the mechanisms through which parental background can influence their children's earnings, that is through the probability of attaining a higher level of education, through the probability of achieving a higher occupational status, through the transmission of human capital (devoting more time to the children or financially),and the network effects that are specially noticeable in Mediterranean countries through labor market imperfections (parachute/glass ceiling effect) (Raitano and Vona, 2015b).

2.3 Descriptive Statistics

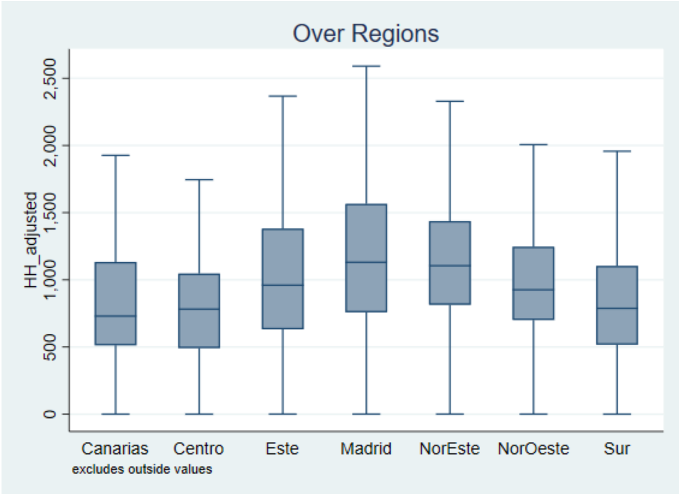
In Figure 2 we present a set of diagrams aimed at helping the reader to have a first sight at the income distribution according to different set of circumstances, circumstances that we will be taking into account for our analysis.
Moreover, and acknowledging the Spanish regional differences, we have divided our dataset in NUTS-1 regions in Figure 1 by *NorEste, NorOeste, Centro, Este, Madrid, Sur, Canarias* [8] where we can derive that those regions with higher income are *Madrid, NoEste & Este* mainly

[6] We have built such index with the variable of promotion of culture plus the parental support of education, such index has a minimum of 1 and a max of 8

[7] Estimations for education include as controls, age, age squared, number of siblings, perceived quality of teachers, municipal population at 16 and dummies for migrant, type of school and presence of both parents. The estimations on occupation and income include as dummies education level, type of school, perceived quality of teachers, age, age squared, municipal level population and dummies on migrant, marriage status and contract type

[8] NorEste: contains the autonomous regions of the Vasc country, Navarra, La Rioja and Aragon. NorOeste: contains the autonomous communities of Galicia, Asturias and Cantabria. Centro: contains the automous regions of Castilla y Leon, Castilla la Mancha and Extremadura. Este: contains the autonomous regions of Catalonia, Balearic Islands and Valencian community. Madrid: is just formed by the autonomous community of Madrid. Sur: contains the autonomous regions of Andalucia and Murcia and Canarias that contains the autonomous region of the Canary Islands

Figure 1: Household Adjusted Income by Regions

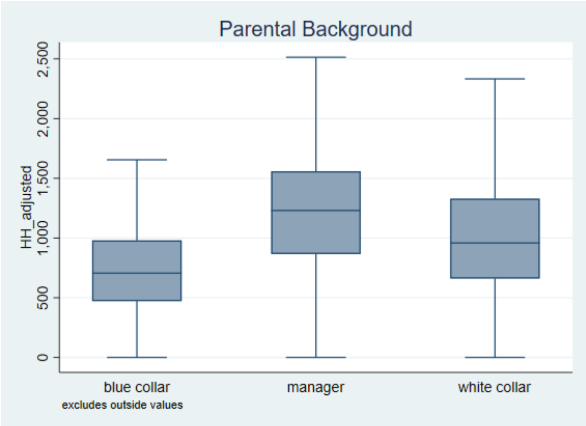


This graph shows groups Household adjusted income by regions. *Canarias*, *Centro*, *Este*, *Madrid*, *NorEste*, *NorOeste*, *Sur*

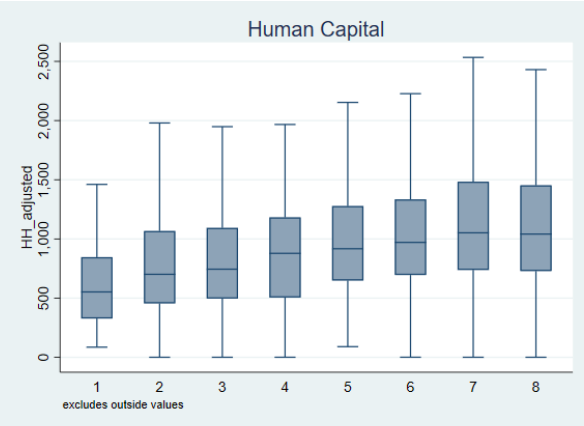
due to the fact of Madrid, Catalonia and Northern regions that have always being above the average. On the other side we find *Canarias, Centro & Sur*, with the lowest incomes in the country. It is worth noticing how even though NorEste has higher average income than Este, the later has a higher top 95%, given the managerial positions in the metropolitan areas of Barcelona, only surpassed by the Madrid data.

In Table 1, we can see that the columns represent highest parental education attainment, and in the rows highers child attainment, in percentages of the total. We have divided educational attainment in 4 main groups following ISCED categories in the following order Primary, Lower Secondary, Upper Secondary non tertiary and finally Tertiary education. As the data show up, there has been an generalized upward mobility in terms of education (corresponding to the values below the main diagonal) where about 55% of the whole sample has had a higher education level than their parents, 27.1% of the sample have had the same education level of their parents and only 17.8% had a lower education than their parents, specially accounting for the increase in education of women (see Appendix 4). This is due to the expansion of the education system that specially enabled women to access higher education.
In Table 2 we show the percentage distribution matrix on occupation, here we can see the inter-generational component in occupation. It is specially noticeable the fact that, there is a strong correlation in occupation around 0.32, stronger than the correlation in education 0.23. And the almost absence of individuals who either their parents where on the top of occupations and they are in the lowest (2.89%) or children who ended up in managerial position

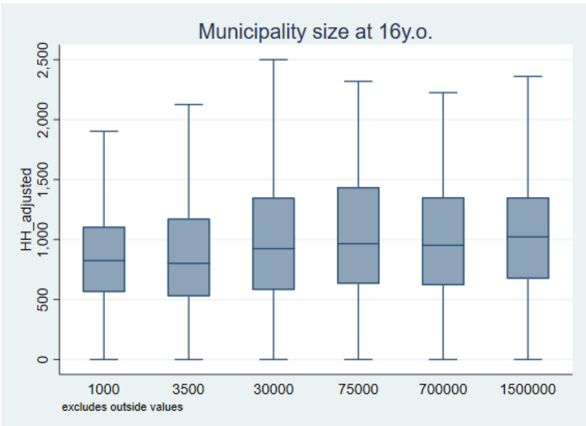
Figure 2: Household Adjusted Income by different characteristics



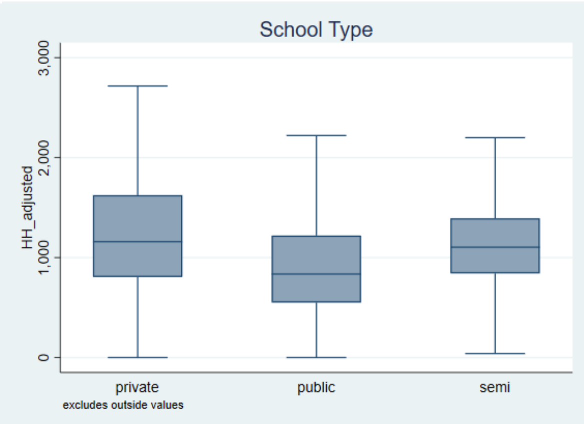
Blue collar are ISCO 6-9, White collar are ISCO 3-5, and managers are ISCO 1-2.



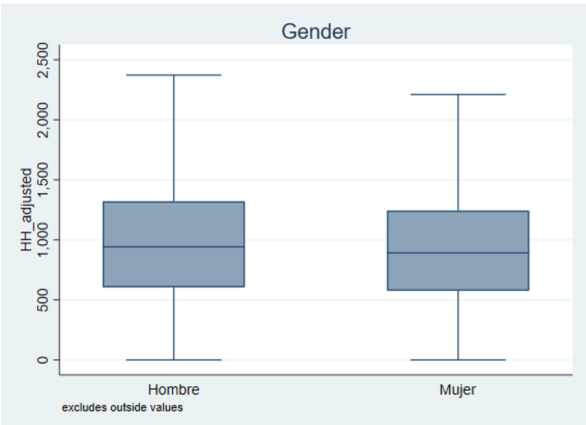
Human Capital Index, with 1 being the smallest HC and 8 being the highest.



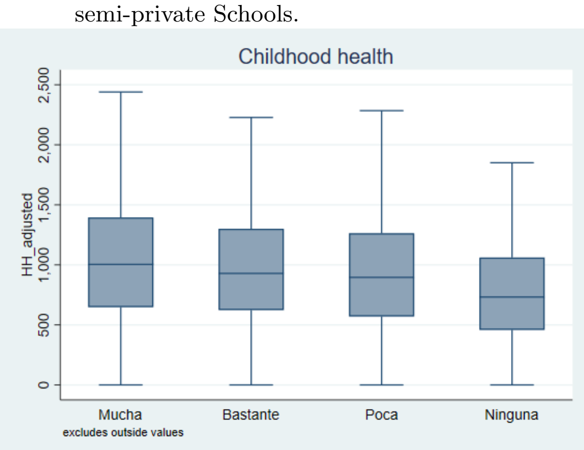
Population of the municipality at 16, where the child studied and the parents worked.



Division made by *priv* meaning Private School, Public School and*semi* meaning semi-private Schools.



Where *Hombre* meaning Man and *Mujer* meaning Woman.



Promotion of healthy habits by the parents, nutrition, sport...

Table 1: Intergenerational Matrix of Education

	Parents Education				
	Primary	Lower Secondary	Upper Secondary	Tertiary	Total
Child Education					
Primary	6.73	0.26	0.19	2.13	9.31
Lowe Secondary	15.98	4.20	2.20	3.88	26.26
Upper Secondary	19.73	7.05	11.77	9.12	47.67
Tertiary	4.72	2.26	5.37	4.40	16.75
Total	47.15	13.78	19.53	19.53	100.00

This table shows on the columns the highest education level attained by the father compared with the highest education level of the children in the rows, following the ISCED categories. The figures show the percentage in respect of the total of each cell

having their parents blue collar jobs (6.51%). Data shows how there exists certain relative inter-generational upward mobility accounting for 31.91%, meanwhile downward mobility accounts for 19.1% of all individuals. Representing that around 1/2 of all individuals have a job in the same category as their parents.

Table 2: Intergenerational Matrix of Occupation

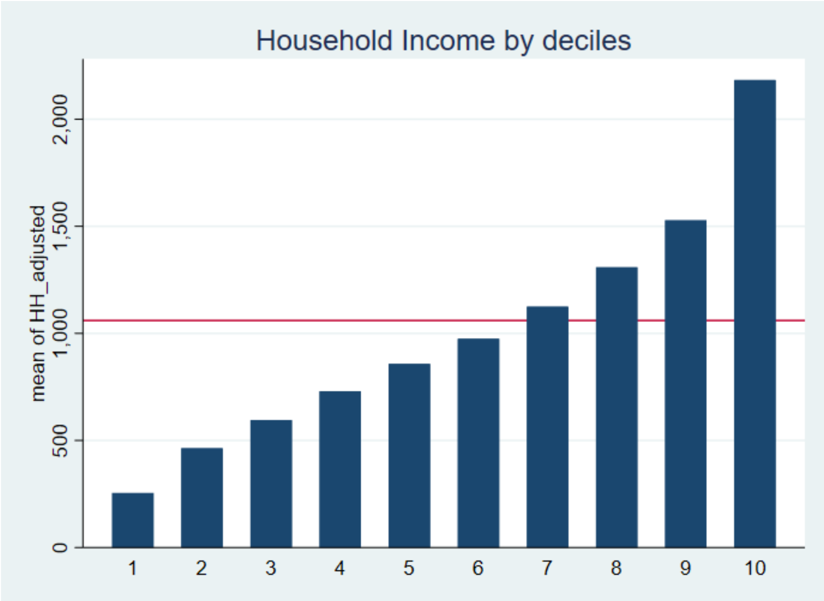
	Parental Background			
	Blue Collar	White Collar	Manager	Total
Child Occupation				
Blue Collar	25.11	8.32	2.89	36.32
White Collar	18.45	16.64	7.89	42.98
Manager	6.51	6.95	7.24	20.69
Total	50.07	31.91	18.02	100

This table shows on the columns the highest occupation of the parents and on the rows the occupations of the children classified as mentioned before. We are seeing the percentage of the total amount in each cell.

It is also worth noticing how income [9] is distributed. Thus in Figure 3 we show the mean income by deciles, where the red line crossing accounts for the 10% share of total income and thus meaning total equality. It out stands immediately the fact that until decile 7, income it is not above the average. Moreover, there is a depression in the first decile that just amounts around 2.53% of national income meanwhile the top decile accounts for more than 21%.

[9] We will use income as a substitute of household adjusted income

Figure 3: Mean Household Adjusted Income by Deciles



This graph shows groups Household adjusted income by deciles and shows the mean income by each decile. Moreover includes a red line showing the 10% of equality of income.

3 Results

3.1 Direct and Indirect Effects

We start by presenting our main results from the direct and indirect effects of parental background on earnings. We have conducted a total of 5 estimations ((1)Direct Effects, (2) Effects through education and its quality, (3) Effects through education, quality and Human Capital, (4) Effects through education, quality, human capital and Occupation and (5) Effects through education, quality, human capital, occupation and social network.) to see the change in effects when adding more controls. For our analysis we have considered only those earning a positive income and we have included a set of control variables such as the Age, Age squared, number of siblings, health at 16, health now, population of the municipality when 16 and dummies for migrant, if both parents where present and Gender. For estimates taking into account the labor market (occupation and social network), we have dropped certain controls such as the municipality or health when 16 and we have included marriage status, current municipality population and if working conditions (self-employed and casual worker). Estimates are shown in the Appendix 4 where we present estimates for both White Collar parents and Manager parents in respect of Blue Collar parents. We can see that both direct effects for middle class parents and high class parents are significantly positive being increasing log earnings by 13% and 41.9% respectively, both estimates are around estimates of total effect of parental background in Raitano and Vona (2015a) being consistent with previous literature. Estimates of channels will be in the 4 in the Appendix section.

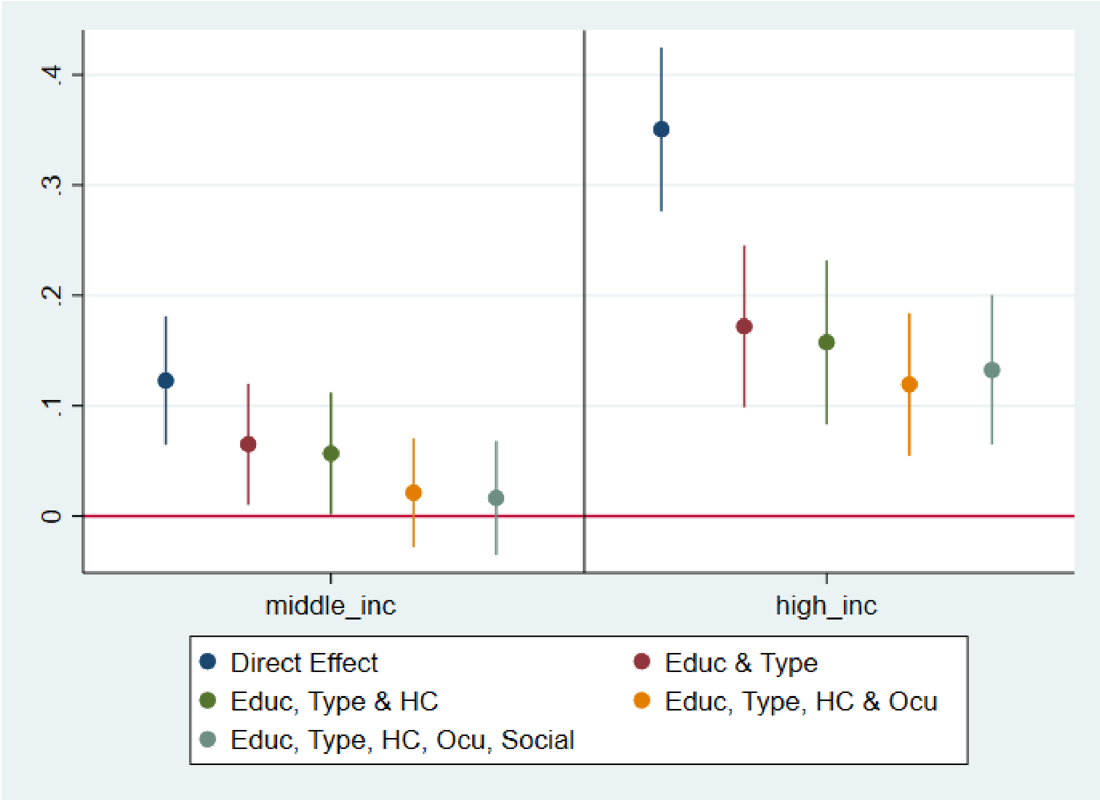
What is a novelty in our field of research is to add certain mechanisms that are linked to parental background in an indirect way such as human capital transmission, school choice (private, semi-private or public) and the social network that have the possibility to influence offspring earnings and that are able to channel the effects of parental background into the next generation. Thus we will now look in detail at the indirect effects of parental background when checking for such variables.

Estimates of model (2) shows the channel through education and its quality (school type). We see that the estimates, of background decrease considerably, meaning that a large transmission of status is through education. Now, *White Collar* parents effect decreases to just 6.72% and it is just significant at 90% similarly, *Managerial* parents remain with an effect of 18.77% on earnings and continues being significant at 99%. Moreover, each ISCED position increase increases income by 27.89% and the effect of private schools are an 14.57% increase while estimates on semi-private schools are non significant.

The following estimates on model (3) take into account the previous model and adds the human capital component, we have considered this step as the variables capturing *Human Capital* are present during the childhood. Thus we see the effect of parental background before including channels of the labor market. Now *White Collar* children still have a 5.87% earning surplus compared to *Blue Collars* again being significant at the 90%. Furthermore, *Manager's* child enjoy a increase in earnings of around 17%, coefficients on ISCED levels, private and semi-prvate schools remain more or less equal as in the previous model. Now, the *Human Capital* channel is significant at 90% with an increase of 1.71%.

When looking at model (4), now we take a new transmission channel which is occupation and a new set of control variables. Now the effect of middle income parents disappears as is no longer significant, but the effect of high income parents is still strong accounting to an increase in earnings of around 12.64% and being significant at the 99%. Once we account for occupation, the effect of education becomes smaller as we should have expected, but still significant. The same way there is a decrease in the influence of private schooling in earnings now just accounting for an increase of around 9%, partly because now occupation is capturing it. Nonetheless, *Human Capital* increases its effect on earnings being now 2.53%.

Figure 4: OLS estimates of Parental Background



OLS estimates of parental background, on households earning a positive income. From the first estimation until the thirds with occupation the we have used as control variables Age, Age squared, Gender, number of siblings, health status at 16, health status now, population of their municipality at 16 and dummies on migrant and if both parents were present. Then, for the last two estimations we have also included as control variables, the population of the municipality, married status, and dummies for casual workers and self-employed.

Finally, in our last model (5) where we account for all possible background circumstances (human capital, quality of education and social networks) and offspring education and occupation. Interestingly, the social network[10] coefficient is negative decreasing earnings by 0.89% every time the social network was more important in achieving the job position. A possible explanation is the parachute effect (Raitano and Vona, 2015b) where individuals have to use their social networks to achieve not their desired job but to avoid being unemployed, thus a lower wage is expected when their social network use is more intense as a sort of insurance cover against unemployment. We can see that still, the effect of parental background is positive giving descendants of high income parents an 14.11% more on earnings than those with a Blue Collar background. This coefficient is even higher when controlling for social network than in model (4) in Figure 4, a possible explanation is that either we are omitting relevant transmission channels or that now that we have disentangled the "insurance" effect to avoid unemployment, parental background is now capturing the trampoline effect where those with their parents belonging to a high income status benefit through their network in other ways that help them achieve a higher income.

3.2 Direct and Indirect Effects by Regions

Now we will put the focus on regional differences and we will compress the 5 models used at the national level towards 3 (1) Total direct effect, (2) indirect effects through characteristics while living at home (education, quality of education and Human Capital) and (3) as in model (2) but including labor market characteristics.

In Figure 5 we can see that out of all regions, only in North East those households which had a middle income background have a 20% lower level of earnings than those with low income background. Then, East region's coefficient is near 0, proving no effect.
On the other side, all high income background total effects are positive being Madrid, Canary Islands and Southern regions the ones with a larger effect, with more than 62%, 57% and 54% respectively. The rest of the estimators range between 20% and 40%. Being again the North Eastern region the one in the lower bound of the distribution.

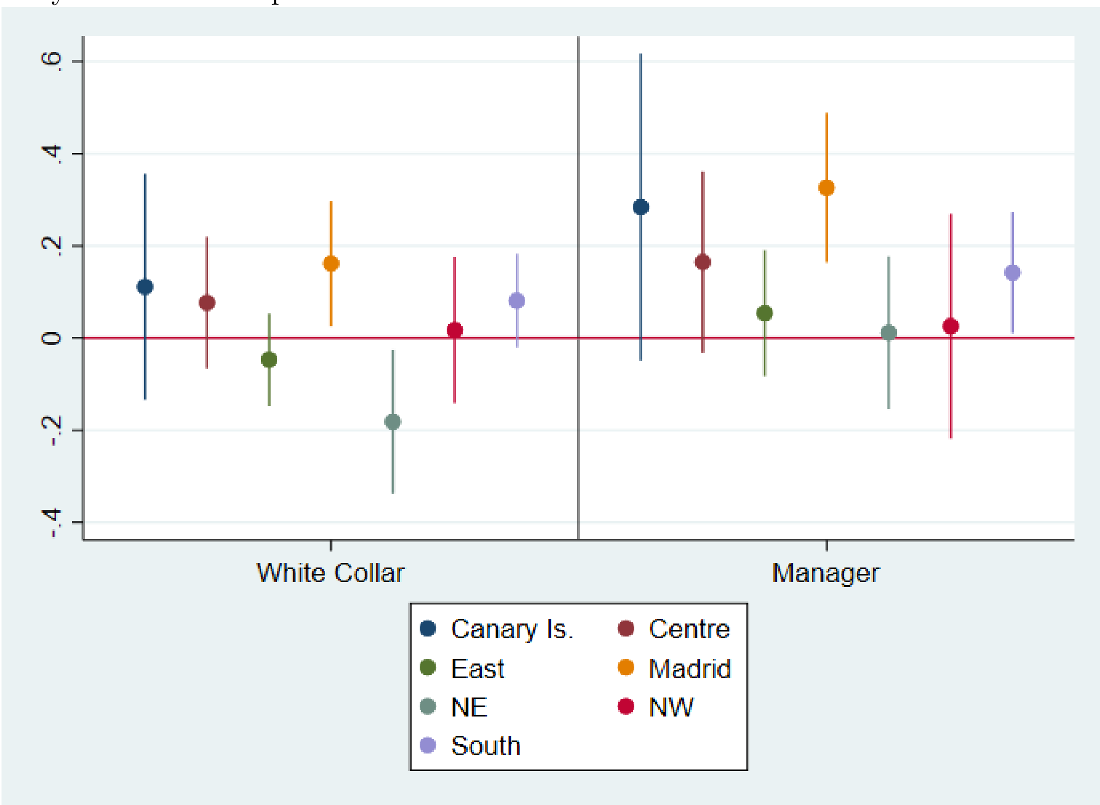
In Figure 6 contrary to Figure 5, almost all coefficients for middle income background are positive or around zero but without any significance level being the Madrid community the only one with a positive significance coefficient, meaning that those with a White Collar background enjoy around 17.5% more of income once discounted the educational, quality of

[10] defined as importance on the respondent social network in achieving its current or last job

Figure 5: Direct effect of parental background by regions

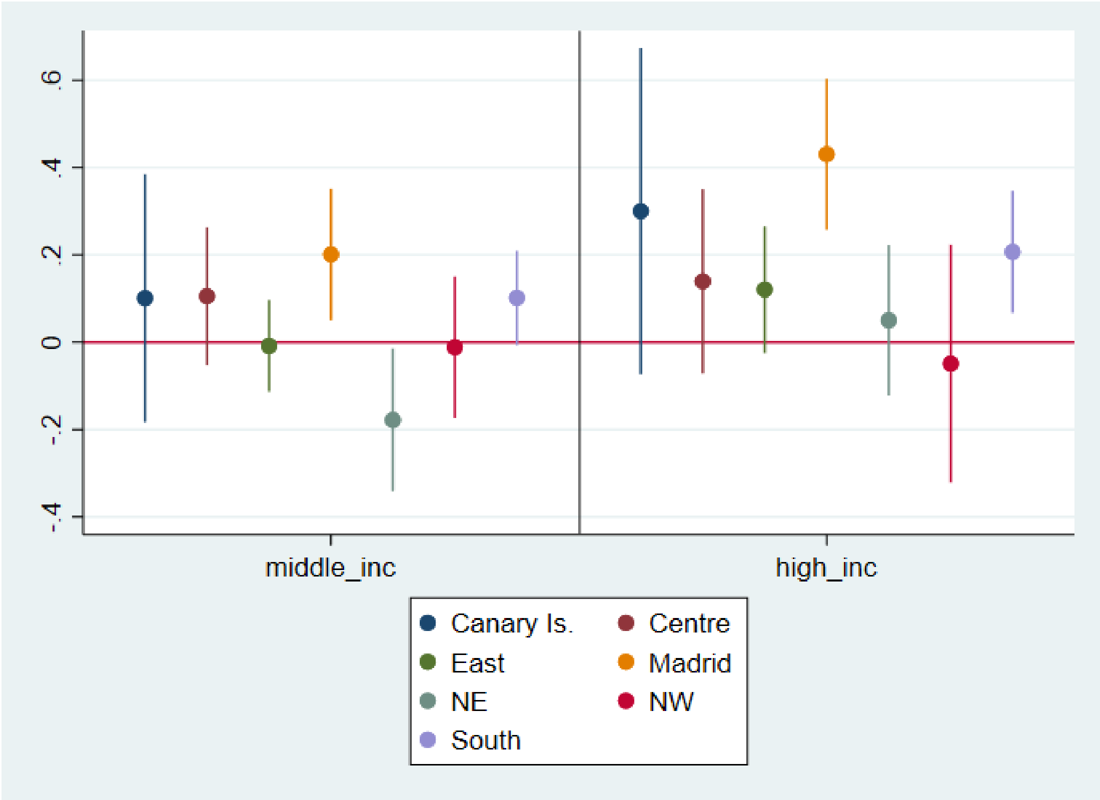
This graph shows the OLS estimators of the direct effect of parental background on households earning a positive income for the NUTS-1 regions of Spain. The controls used are, Age, Age squared, number of siblings, health habits at 16, health status, and dummies for migrant and if both parents where in the house.

Figure 6: Indirect Effect of Parental Background on Earnings controlling for Education, Quality and Human Capital



This graph shows the OLS estimators of parental background on households earning a positive income for NUTS-1 regions of Spain. It shows the indirect effects through childhood, that is education, quality of education and Human Capital. Control variables include, Age, Age squared, number of siblings, health habits at 16, health status, and dummies for migrant and if both parents where present.

Figure 7: Indirect effect of Parental Background controlling for Education, Quality, Human Capital, Occupation and Social Network



This graph shows the OLS estimators of parental background on households earning a positive income for NUTS-1 regions of Spain. It shows the indirect effects through childhood, that is education, quality of education and Human Capital and through adulthood through occupation and social network. Control variables include, Age, Age squared, number of siblings, health status, population of the municipality and dummies for migrant and if both parents where present, married status, casual worker and self-employed.

education and human capital channels. Again, North East estimates are negative for middle income background, with 20% lower income than those with a lower level in background status.
Moreover, when we look at the coefficients for Managerial background, and similarly to those coefficients of middle income background, most of them lose their significance level, except of Madrid and Southern region, where having a Managerial background enables them to have 50% and 15% higher earnings than those of Blue collar background.

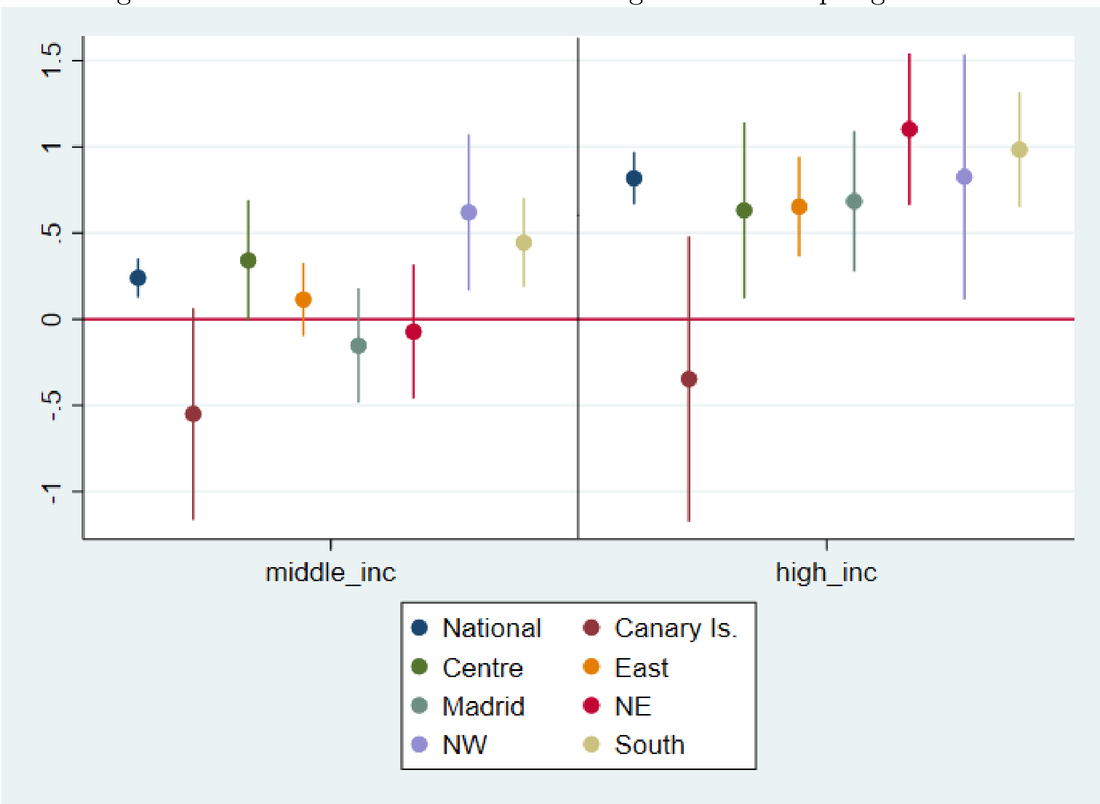
To conclude with our regional analysis, we will study the indirect effect of parental background once deducted all transmission mechanisms. Thus in Figure 9 we see that the same patterns of regional classification by parental background effects remain.
For middle income background in North Eastern regions the decrease in earnings is now around 16% the lowest decrease out of all 3 estimations. Meanwhile, Madrid's middle income background individuals are enjoying a 22.3% higher earnings than the low parental background individuals.
It is interesting to see how coefficients vary regionally from model (2) to the current model. Madrid & Southern regions with statistically significant effects of 53.8% and 23%, increase their impact from the previous model by 7% and 41% respectively, but also Eastern regions (although not being statistically significant). On the other side we have regions (although not being statistically significant) such as North West and Centre whose coefficients decreased, even arriving to be negative for North Western regions. This differentiation in patterns could be explained by two reasons, firstly in the region of Madrid where there are a lot of top positions as economic centre of Spain, making that being born in a top family makes it easier to remain there with the advantage of the wage premiums paid to such positions in such economic hub. On the other side, Southern regions, that have a more rigid social structure given historical traits may benefit more from the parachute effect of non competitive labor market dynamics and thus continue benefiting from their background effects.

It is worth noticing the limitations of our analysis given the low amount of observations in certain regions, thus some of our estimates and conclusions may suffer from a large bias. Future research could develop on how to structure social network effect to be able to properly capture the "insurance" effect of social networks in the labor markets, but also the trampoline effects, that enable children of well-off families to jump and skip certain steps in the labor market making it easier for them to achieve higher positions and higher income.

3.3 Ordered Probit Coefficients

Following our analaysis we show in Figure 8 the Ordered Probit Coefficients for parental background in the case of education, where we can clearly observe how while average effects at the National level are positive for both middle income and high income backgrounds, at the regional level there exists heterogeneity, specially regarding the middle income group. For the high income group they are all positive and statistically significant except for the Canary Islands where the effect is surprisingly negative but non significant.

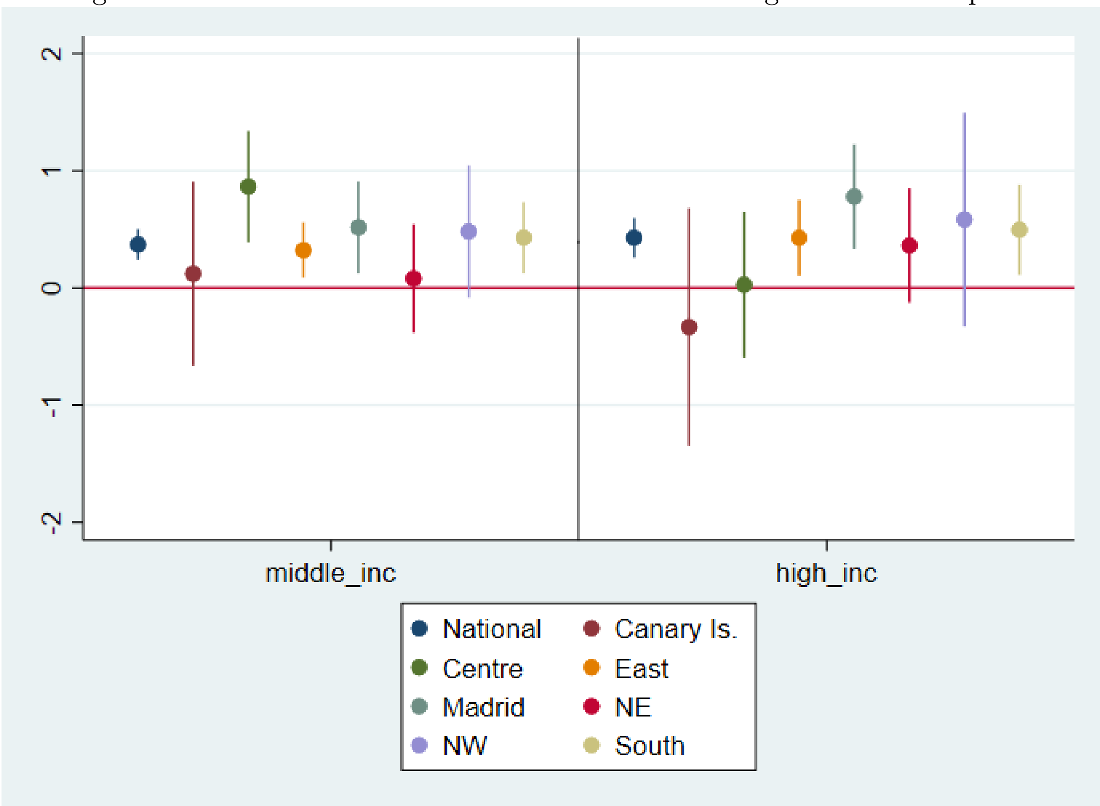
Figure 8: Orderer Probit of Parental Background on Offspring Education



This graph shows the Ordered Probit estimators of parental background on households earning a positive income for Spain and its NUTS-1 regions. Control variables include, Age, Age squared, number of siblings, health status, population of the municipality and dummies for migrant and if both parents where present.

Once again, at the national level we do have a positive and significant effect of parental background on occupation being the same size both for individuals whose parents were white collars and managers. Then once again at the regional level there exist heterogeneity and the smaller samples increase the standard errors making most of the coefficients non significant.

Figure 9: Ordered Probit Coefficients of Parental Background on Occupation



This graph shows the Ordered Probit Coefficients of parental background on households earning a positive income for Spain and its NUTS-1 regions. Control variables include, Age, Age squared, number of siblings, health status, population of the municipality and dummies for migrant and if both parents where present, married status, casual worker and self-employed.

These results, add robustness to our previous estimates of the direct and indirect effects proving that parental background also do have an impact on education and occupation. And that those who have a better socioeconomic background have better chances to achieve higher education and better occupations that would increase the potential income.

3.4 Relative Importance of the Channels

To conclude with our analysis we can see on Table 3 the coefficients and relative importance of the main channels of transmission of inequalities, we have excluded control variables from the table but they are visible at Appendix 4. We can see how for offspring education the status of parental background matters the most jointly with the Human capital promotion from the parents. They account for 50% of the explanatory power of the model. Moreover, see show how Human Capital promotion is also linked to the status of the parents in Appendix 4, thus enhancing the idea that parental background is a key determinant of educational success of the children. We can also see that household size and attending to a private school also have an important influence on offspring education.

When looking at offspring occupation it is surprising how human capital becomes non significant, while being the major factor for educational achievement. This means that all the effect from human capital it is absorbed by education and this has no longer an effect in the labor market as now education is the signal for human capital acquisition for the individual. Moreover, we see how education level is now the main determinant of occupation accounting for more than 55%. Despite accounting for education we see how attending to a private school has a positive impact in determining occupational status, in the same direction as parental background for those individuals whose parents belonged to middle and high incomes. Noticeably, social networks have as mentioned before a negative impact on incomes through the so called *insurance effect* here we see how in the same line, social networks affect the same way occupational status, because those who had to make use of their networks to achieve a job had a lower occupational position in the labor market.

Finally, when looking at incomes, only high income parental background remains positive and accounts for 6.51% of the explanatory power of the model. Private education continues being a source of inequality, and the social network effect goes as explained previously in Section 3.1. As expected, educational attainment and occupational status are the main drivers of income, although much of the variance of income is not explained by our model.

4 Conclusion

We find that even by taking into account all channels through which parental background may exert its influences. Being born in a high income family delivers a positive influence on

Table 3: Coefficients and relative importance of transmission channels

	Offspring Education	Offspring Occupation	Offspring Income
middle_inc	0.166*** (0.045)	0.195*** (0.041)	0.012 (0.053)
	2.54%	4.21%	0.24%
high_inc	0.498*** (0.058)	0.235*** (0.053)	0.164** (0.070)
	23.93%	9.17%	6.51%
HC	0.088*** (0.012)	0.007 (0.010)	0.010 (0.012)
	26.23%	5.84%	4.90%
priv	0.314*** (0.059)	0.185*** (0.053)	0.143** (0.069)
	9.29%	5.07%	3.86%
HH size	-0.060*** (0.009)		
	13.48%		
social network		-0.017*** (0.004)	-0.010* (0.006)
		5.35%	3.21%
ISCED		0.360*** (0.024)	0.179*** (0.034)
		55.22%	25.50%
ocupacion			0.155*** (0.037)
			21.91%
_cons	0.901** (0.383)	0.897*** (0.100)	6.292*** (0.135)
N	1399	1226	1226
R^2	0.270	0.322	0.187

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Relative importance of each variable under betas.

For each regression we include the same control variables as used in the previous models.

income of more than 14% compared of those born in families with scarce resources. In the same way this parental background effect takes place through different channels, all of them being relevant for the offspring earnings (except human capital that is channeled through education). An interesting field of future research specially on social networks, and its effects depending on parental background as the power of social networks may change across different social positions as well as its functions. Also, it is an important field for future research the role of schools & universities we think there may be heterogeneity in their role (some more labor oriented, some more academia oriented) . It is also worth mentioning the limitations of our analysis due to the reduced sample size, and the fact that we had to construct arbitrary measures for human capital. Thus, our estimates could be biased in the way we have constructed our variables.

At the regional level we see that Madrid and Southern regions effects are larger, probably due to the fact of the wage premiums in the capital and the society structure in the latter.

In terms of policy implications, we can also hinder that in Madrid where there is a higher concentration of private schools the channels of social networks and occupational choice may have a stronger effect due to selection. Thus, being able to support with sufficient financing and quality a public educational system may result in a reduced influence of parental background and a levered playing field for everyone. Moreover, a more efficient labor market may result in a decrease of parental background effects and social network differentials. Policies that may encourage transparency in the hiring process through matching webs (Linkedin, Infojobs...) may result in a fairer labor market dynamics, enhancing efficiency, fairness and growth. To finish, to try to solve the channels of inequality of opportunity has positive impacts not only in the economic performance of a society but also for the social scene. These policies may encounter certain restrictions through the political economy given the effects of interested parties in the decision making of politics.

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Appendix

	(1)
	HC
middle_inc	0.667***
	(0.114)
high_inc	1.270***
	(0.143)
padres	-0.033
	(0.173)
priv	0.783***
	(0.147)
semi	0.458***
	(0.155)
Age	0.042
	(0.045)
Age2	-0.001*
	(0.001)
migrant	-0.038
	(0.159)
bros	-0.128***
	(0.022)
_cons	4.868***
	(0.944)
N	1402
R^2	0.181

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Intergenerational Matrix of Education

	Mother Education				
	Primary	Lower Secondary	Upper Secondary	Tertiary	Total
Women Education					
Primary	7.97	0.28	0.43	1.00	9.67
Lowe Secondary	17.07	3.13	1.42	1.14	22.76
Upper Secondary	27.74	7.40	10.81	3.56	49.50
Tertiary	6.54	2.99	5.97	2.56	18.07
Total	59.32	13.80	18.63	8.25	100.00

This table shows on the columns the highest education level attained by the father compared with the highest education level of the children in the rows, following the ISCED categories. The figures show the percentage in respect of the total of each cell

Table 5: Household adjusted Income by Cohorts

	Mean	SD	Min	Max	N
Cohorts					
25-29	1,007.44	550.82	169.55	4,613.68	174.00
30-34	1,100.11	646.09	0.67	3,976.78	175.00
35-39	1,061.48	591.44	0.48	3,571.43	221.00
40-44	1,089.34	506.31	0.67	3,313.61	275.00
45-49	925.75	511.99	0.50	2,869.31	223.00
50-54	930.90	593.77	0.40	4,368.23	236.00
55-60	894.71	527.87	0.40	4,426.60	220.00
Total	1,000.62	563.72	0.40	4,613.68	1,524.00

This table shows the average household adjusted income by cohorts, for more information we have disclosured also the standard deviation also the minimum and the maximum values, plus the total amount of observations

Prediciton of Household Income

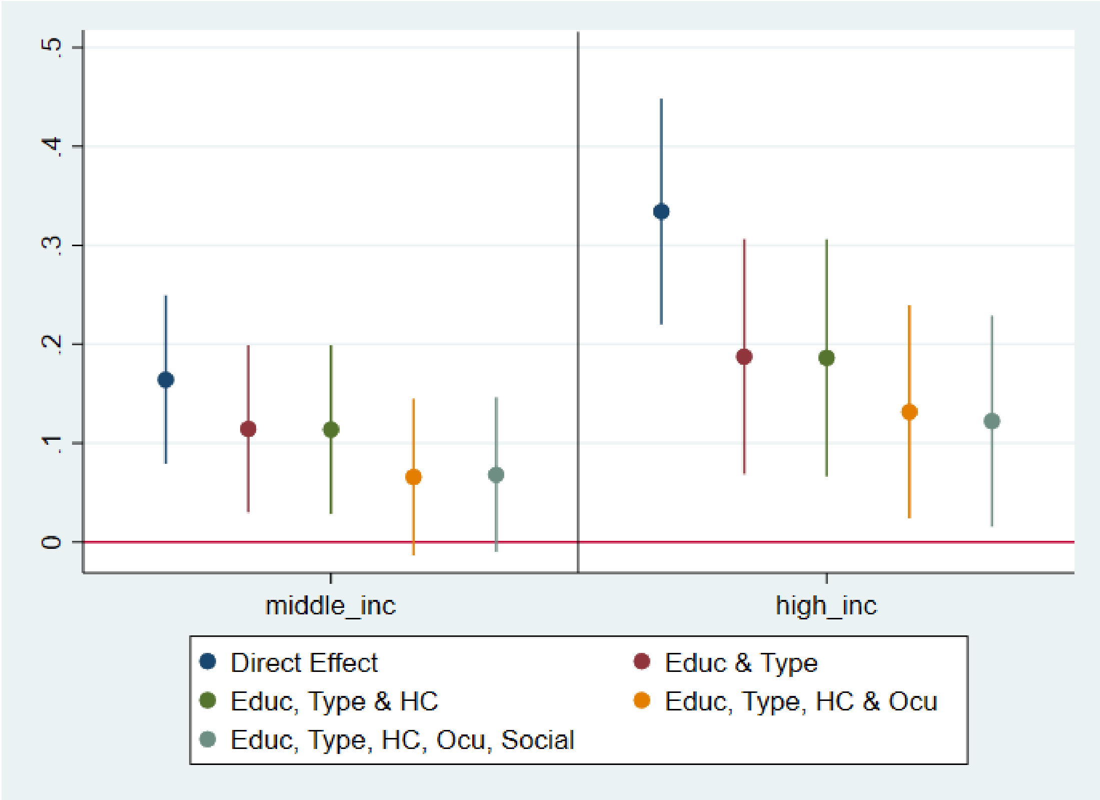
	Prediction HH_inc	
HH_size	292.982***	(65.337)
high_inc	281.858***	(107.537)
middle_inc	45.517	(79.711)
ISCED	191.356***	(51.476)
Sex	227.658***	(86.793)
ocupacion	375.929***	(54.493)
priv	341.430***	(103.900)
semi	-10.390	(111.024)
P33	36.982	(33.734)
Age2	-0.421	(0.391)
health	-93.015**	(42.003)
migrant	-498.363***	(111.463)
casado	342.501***	(82.598)
autonomo	9.559	(124.004)
eventual	323.195***	(75.766)
familiar	1.702	(114.242)
bros	-32.747**	(15.809)
social	-155.603*	(81.249)
municipio	0.000	(0.000)
HC	33.612*	(20.021)
P6_2	-56.697	(38.855)
hijos	139.184	(118.058)
menores	-217.354***	(82.046)
1.regions	0.000	(.)
2.regions	25.393	(189.543)
3.regions	332.939*	(172.657)
4.regions	470.490**	(189.537)
5.regions	489.853**	(198.378)
6.regions	203.805	(199.171)
7.regions	65.360	(174.889)
_cons	-1376.338*	(746.515)
N	943	
R^2	0.332	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimations with Individual Income

Figure 10: Indirect effect of Parental Background controlling for Education, Quality, Human Capital, Occupation and Social Network



This graph shows the Ordered Probit Coefficients of parental background on households earning a positive income for Spain and its NUTS-1 regions. Control variables include, Age, Age squared, number of siblings, health status, population of the municipality and dummies for migrant and if both parents where present, married status, casual worker and self-employed.

Estimates for the household level

	(1)	(2)	(3)	(4)	(5)
	ln_income	ln_income	ln_income	ln_income	ln_income
middle_inc	0.123***	0.068*	0.061*	0.027	0.019
	(0.037)	(0.035)	(0.035)	(0.031)	(0.033)
high_inc	0.359***	0.188***	0.178***	0.142***	0.154***
	(0.047)	(0.047)	(0.047)	(0.041)	(0.043)
Age	0.061***	0.047***	0.048***	0.014	-0.002
	(0.015)	(0.014)	(0.014)	(0.012)	(0.013)
Age2	-0.001***	-0.001***	-0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex	-0.028	0.012	0.013	0.077**	0.095***
	(0.040)	(0.038)	(0.038)	(0.033)	(0.035)
migrant	-0.135**	-0.193***	-0.189***	-0.225***	-0.207***
	(0.054)	(0.052)	(0.052)	(0.044)	(0.047)
bros	-0.064***	-0.044***	-0.043***	-0.035***	-0.036***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
padres	0.016	-0.007	-0.003	0.010	-0.002
	(0.059)	(0.056)	(0.056)	(0.047)	(0.049)
health at 16	-0.076***	-0.058***	-0.048**		
	(0.018)	(0.017)	(0.019)		
health	-0.077***	-0.073***	-0.073***	-0.061***	-0.051***
	(0.020)	(0.019)	(0.019)	(0.017)	(0.018)
mun_antiguo	0.000*	0.000	0.000		
	(0.000)	(0.000)	(0.000)		
ISCED		0.235***	0.231***	0.145***	0.143***
		(0.020)	(0.020)	(0.020)	(0.021)
priv		0.141***	0.135***	0.094**	0.078*
		(0.048)	(0.048)	(0.040)	(0.042)
semi		-0.002	-0.005	-0.008	0.011
		(0.050)	(0.050)	(0.042)	(0.045)
HC			0.011	0.026***	0.026***
			(0.009)	(0.007)	(0.008)
ocupacion				0.177***	0.163***
				(0.021)	(0.023)
casado				0.117***	0.139***
				(0.029)	(0.030)
municipio				0.000	0.000
				(0.000)	(0.000)
eventual				0.259***	0.273***
				(0.030)	(0.032)
autonomo				0.118***	0.129***
				(0.045)	(0.048)
social n					-0.008**
					(0.004)
_cons	5.955***	5.480***	5.404***	5.587***	5.992***
	(0.309)	(0.294)	(0.299)	(0.262)	(0.287)
N	1184	1184	1183	1362	1217
R^2	0.184	0.280	0.281	0.368	0.374