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# **Sometimes you cannot make it on your own. How household background influences chances of success in Italy\***

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## **Abstract**

In this paper, we explore channels by which household background determines an individual's educational and social opportunities in Italy. Our analysis relies on a rich dataset that contains data both on individuals and their real parents, as well as information on individuals' non-cognitive skills. This paper also represents the first attempt to evaluate if and to what extent personality traits affect educational and occupational opportunities in Italy and how they interact with household background. The results highlight that the level of parental education is more relevant than the level of parental occupational skill in individuals' educational and social opportunities. The inclusion of 'Big-5' variables in the model helps control for omitted variables and reduces the unobserved heterogeneity in intergenerational social mobility among individuals with the same level of education and skills. Our results depict a dual and unequal labour market.

**Keywords:** intergenerational mobility; equality of opportunity; household background; regional studies; personality traits; big five.

**JEL Classification:** I24, J62, R23.

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*Can you hear me when I sing?  
You're the reason I sing  
You're the reason why the opera is in me  
...  
Sometimes you can't make it on your own*

Hewson Paul David

## 1. Introduction

Several studies highlight that the level of inequality in the income distribution often represents an incomplete criterion to assess fairness in a modern society (Dworkin 1981; Arneson 1989; Cohen 1989; Ferreira and Gignoux 2008). In this field of literature, the portion of inequality considered completely unacceptable depends on the circumstances (e.g. household background, gender, or race) in which an individual is located. John Roemer (1998) defines this inequality component as the ‘inequality of opportunity’. When the inequality of opportunity reaches a high level, a society seems to remain ‘petrified’ in a pre-established order and the range of opportunities provided to the youth is almost completely bound by the circumstances in which she was born and raised.

Household background has often been identified as an important predictor of the future social conditions of individuals because it affects a large number of aspects regarding their living standards. For instance, household background significantly affects the neighbourhood or the residence area in general (Chetty et al. 2016; Chetty and Hendren 2018a) and access to quality education (Plug 2004). As a further and worse consequence, low levels of equality in terms of opportunities may lead to a loss of human capital for the entire society and to incomes not reflecting individual efforts (Ferreira and Gignoux 2008). The latter, in particular, may appear as ethically controversial to a large portion of the population.

In the current study, the information contained in the Eighth Survey on Labour Participation and Unemployment (INAPP-PLUS 2018) dataset allows us to measure the relevance of both educational and social backgrounds of older generations on their offspring’s school career and working life in Italy, and to test within-country heterogeneity. We consider this country an interesting case study because among European countries, Italy is characterized by very low levels of social mobility (Breen and Luijkx 2004; Corak 2013) and by a lasting North–South dualism in the labour market (Daniele and Malanima 2013). Another important feature of the dataset is that it contains data on educational level attained and the ISCO-08 rank (i.e. a classification of the complexity and range of tasks and duties performed in an occupation) for both interviewed people and their real parents. Due to the lack of available data, most of the empirical literature on intergenerational mobility is limited to estimating pseudo-intergenerational mobility, i.e. the association between individuals belonging to subsequent cohorts (e.g. Güell et al. 2018; Barbieri et al. 2019). In this analysis, we consider intergenerational mobility as the individual ability to obtain the tools to succeed in the labour market (i.e. high education level) or of overcoming the ‘glass ceiling’ (i.e. high occupation skill level) independently of household background.

To develop the econometric analysis, we run Probit models on two different samples according to the outcome. Indeed, we refer to the entire population when we look at individual educational opportunities (i.e. the highest level of education attained), whereas we only focus on workers when we investigate the effect of parental background on individual social opportunities (i.e. highest level of occupational skills attained). Our study focuses on the ‘glass ceiling’ as it particularly harms social mobility in Italy. Nevertheless, in Section 6 we conduct robustness checks disaggregating data to each level of education and skills.

Furthermore, we explore the moderating role of personality traits, which are rarely observed in survey data, on the relationship between household background and individuals’ educational and social opportunities. Understanding how much children differ in terms of these traits is important as scholars have devoted significant efforts to developing models to overcome selection bias due to unobservable characteristics when estimating the impact of parental background on labour market outcomes. In other words, the inclusion of non-cognitive skills allows us to minimize the set of omitted variables, thus reducing the unobserved heterogeneity among individuals with the same level of skills (Blasquez and Budria 2012). Specifically, thanks to the same INAPP-PLUS 2018 dataset, we can build the well-known ‘Big-5 model’ for Italy. This model is the most prevalent personality framework in the literature (Borghans et al. 2008)

and combines a large number of traits into five broad trait domains: openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability or neuroticism.

Finally, following suggestions by Chetty et al. (2014), Chetty and Hendren (2018b), and Corak (2019), a further objective of our study is to stress the importance of within-country heterogeneities in intergenerational mobility. This aspect represents a particular source of concern in Italy because of the territorial divides characterizing this country (Barbieri et al. 2019). We therefore try to identify to what extent inequality of opportunity changes across Italy, both in terms of access to tertiary education and the acquisition of skills in the labour market.

To sum up, the contribution of our paper to the existing literature on the topic is threefold. First, we provide new updated evidence on intergenerational mobility in Italy by estimating the impact of household background on a multidimensional outcome, keeping other significant factors constant. Second, this paper represents the first attempt to investigate the moderating role of personality traits in the drivers of intergenerational mobility. Third, we disaggregate our analysis among the Italian macro-areas to analyse within-country heterogeneity. Moreover, the advantage of using information on individuals' real parents instead of on pseudo-parents, which is used in many articles in the literature, is not negligible. Our study may thus represent an important starting point to improve policy proposals, tailored to regional contexts, to increase intergenerational mobility in Italy.

The remainder of the paper is organized as follows. Section 2 relates the study to the literature. Section 3 discusses the data and definitions of the variables of interest. Section 4 shows a descriptive analysis, while Sections 5 and 6 present the econometric results and robustness checks. Section 7 offers some concluding remarks.

## 2. Literature review

### 2.1. Previous evidence on intergenerational mobility

The empirical economics literature on intergenerational mobility has mainly focused on the United States (among the most recent and most important contributions are Chetty et al. 2014; Chetty et al. 2016; Chetty and Hendren 2018a, 2018b; Palomino et al. 2018; Chetty et al. 2020). Apart from the US, this issue has, however, started to be investigated in many European countries, including Germany (Schnitzlein 2016), France (Bourdieu et al. 2019), Spain (Cervini-Plá 2015), Sweden (Österberg 2000), and the UK (Nicoletti and Ermish 2008; Karagiannaki 2017; Gregg et al. 2019).<sup>5</sup> Comparative studies between European countries have also been carried out (Raaum et al. 2007; Raitano and Vona 2015a, 2015b; Raitano et al. 2016). De Philippis and Rossi (2020) show that among OECD countries, students within the same host country whose parents come from countries with high scores on the PISA test perform better than their peers with similar household backgrounds. To the best of our knowledge, intergenerational mobility in Italy has only been analysed through unidimensional measures of transmission of household background (i.e. education level, type of occupation, and income) due to data limitations (Solon 2002), while just a few papers have studied it considering multiple measures but outside of Italy (Lubotsky and Wittenberg 2006; Vosters and Nybom 2017; Vosters 2018).

As indicated by previous research, the lack of social mobility in Italy appears to mainly depend on the well-known 'glass ceiling', which on the one hand protects the upper class from falling down and, on the other hand, prevents other classes from reaching the higher one. Barone and Mocetti (2016) document this by linking the surnames of individuals who lived in Florence in 1427 to their pseudo-descendants in 2011. The authors' results highlight that the earnings elasticity across generations six centuries apart is positive and statistically significant and that there is strong persistence in some elite professions. Mocetti (2007) uses the two-sample two-stage least-squares method to overcome the absence of an appropriate data set. He shows that intergenerational mobility is lower in Italy compared to other industrial countries. By adopting the same methodology as Mocetti (2007), Piraino (2007) finds that the transmission of economic status is greater at the top of the income distribution. Checchi et al. (2013) explore sources of the intergenerational persistence of education, showing that this phenomenon is due to a larger probability of obtaining a college degree for Italian children with highly educated fathers. Acciari et al. (2019), using administrative data on tax returns, reach

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<sup>5</sup> A few studies have also concentrated on Australia (Leigh 2007), Singapore (Ng 2007), Japan (Ueda 2009), Taiwan (Kan 2015), China (Gong et al. 2012; Deng et al. 2013; Yuan 2017), India (Azam 2016), Brazil (Dunn 2007), and some African countries (Bossuroy and Cogneau 2013).

similar results suggesting that intergenerational mobility is lower among the wealthiest households with respect to others. Moreover, their study also investigates territorial divides in Italy, pointing out the presence of a higher level of social mobility in the northern regions. Güell et al. (2018) and Barbieri et al. (2019), using pseudo-parents, also focus on the within-variation of income-based intergenerational mobility among Italian macro-areas, concluding that it differs considerably throughout the country. The first study finds increasing social mobility proceeding from the south to the north of Italy, whereas the second affirms that the lowest social mobility is found in the islands and northwestern areas, and that the persistence of fathers' and sons' earnings is lowest in the centre of Italy. Chise et al. (2020) detect a sizeable intergenerational transmission of STEM (science, technology, engineering, and mathematics) education. These early studies seem to suggest that understanding the territorial heterogeneity of intergenerational mobility is important in order to draw up policy suggestions aimed at improving social mobility in the country.

Checchi et al. (1999) compare income mobility between Italy and the United States, recognizing the school system as its main determinant. Similarly, in their discussion of an 'education-based meritocracy', Goldthorpe and Jackson (2008) posit three requirements for moving towards a less class-based society: i) the link between social origin and the schooling of individuals must increasingly reflect their abilities only; ii) the link between schooling and employment of individuals must be strengthened by qualifications acquired through their education; iii) the link between schooling and the employment of individuals must become constant for those with different social origins. In this paper, we perform model regressions similar to Checchi et al. (1999) to understand the main bottlenecks affecting social mobility in Italy. Nonetheless, since there is no univocal consensus about the best definition or measure of social mobility (Stuhler 2018), taking advantage of the abovementioned Goldthorpe and Jackson (2008) requirements we define the outcome of social mobility in two different dimensions: a) the highest level of education attained, namely the opportunity to gain skills to progress through society (OECD 2018a); b) the highest occupational skill level attained, which from a sociological point of view defines one's social condition (see, for example, Erikson and Goldthorpe 1992 and Goldthorpe and Heath 1992).

## 2.2. *The role of personality traits in the labour market*

While the literature on intergenerational mobility is growing (D'Addio 2007), empirical studies of the impact of personality traits on this phenomenon are still scant (Osborne Groves 2005), although newsworthy: *'a deeper understanding of personality traits promises to enrich economic theory and to understand the sources of, and solutions for, human inequality'* (Borghans et al. 2008:1038).

Recently, economists have started to focus on the importance of non-cognitive skills in determining labour market outcomes (Carneiro et al. 2007; Borghans et al. 2008; Heckman and Kautz 2012; Fletcher 2013; Cobb-Clark 2015; Caliendo et al. 2019; Golsteyn and Magnée 2020).<sup>6</sup> It is indeed well recognized that personality traits are strong predictors of socioeconomic success (Heckman and Rubinstein 2001; Borghans et al. 2008; Almlund et al. 2011). Heckman et al. (2006) find that non-cognitive skills are at least as relevant as cognitive abilities in determining a number of adult outcomes.

Further research has also highlighted that personality traits are important determinants of unemployment (Caliendo et al. 2015; Cuesta and Budria 2017; Egan et al. 2017; Engelhardt 2017) and overeducation (Blasquez and Budria 2012) as they influence both educational and employment choices (Koch et al. 2015).<sup>7</sup> Lindqvist and Vestman (2011) use data based on personal interviews conducted by a psychologist during the Swedish military enlistment exam and find that both cognitive and non-cognitive abilities are relevant in the labour market, but for different outcomes: low non-cognitive abilities are more associated with unemployment or low earnings, while cognitive ability is highly correlated with wages for skilled workers. Segal (2013) adopts data on young men from the US National Education Longitudinal Survey and finds that eighth-grade misbehaviour is relevant for earnings over and above eighth-grade test scores.

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<sup>6</sup> For a review of the recent empirical literature on the relative importance of non-cognitive skills for school and labour market outcomes, with a focus on Europe, see Brunello and Schlotter (2011).

<sup>7</sup> Personality traits also affect geographic mobility (Buetikofer and Peri 2017). Specifically, high levels of extraversion and openness have a positive and significant effect on migration (Crown et al. 2020).

Looking at child socio-emotional traits, Conti et al. (2010, 2011) show that children's cognitive traits are stronger predictors of employment and wages than socio-emotional traits or early health.<sup>8</sup>

Looking at the role of single personality traits, the literature does not agree on the results: Schmidt and Hunter (2004), Chamorro-Premuzic and Furnham (2005), and Roberts et al. (2005) show that conscientiousness is the best predictor of years of education. Borghans et al. (2008) indicate openness to experience as relevant in determining the education level of individuals. Loehlin (2005) finds that across 47 different studies, openness to experience is the trait with the highest intergenerational correlation.

Since personality traits are important factors for success in the labour market (Loehlin 2005; Borghans et al. 2008; Corak 2013), it is likely that they contribute in a non-negligible way to outcomes of intergenerational mobility (Bowles et al. 2001; Bowles et al. 2005). Thus, including personality traits as additional covariates allows us to control for the influence of the behaviours, thoughts, and emotions of individuals (McCrae and Costa 1987) on intergenerational mobility.

### 3. Data and methods

#### 3.1. Data

The analysis relies on data from the Eighth Survey on Labour Participation and Unemployment (PLUS), which is a sample survey developed and provided by the National Institute for the Analysis of Public Policies (INAPP).<sup>9</sup> The primary objective of the INAPP-PLUS survey consists in providing reliable statistics on phenomena (e.g. intergenerational mobility) rarely or marginally explored by other surveys on the Italian labour market (e.g. the Labour Force Survey or the Survey on Income and Living Conditions, both administered by Eurostat). The survey was collected in 2018 on a representative sample of about 45,000 individuals aged 18–74 and released in the first half of 2019.<sup>10</sup> One of the key characteristics of the INAPP-PLUS dataset is the absence of proxy interviews: in the survey, only survey respondents are included to reduce measurement errors and partial non-responses. Similarly to other empirical studies relying on the same dataset (see, among others, Filippetti et al. 2019; Esposito and Scicchitano, 2020; Meliciani and Radicchia 2011, 2016; Van Wolleghe et al. 2019; Bonacini et al. 2021a; 2021b), all descriptive statistics and estimates reported in this analysis are weighted using individual weights provided in the dataset, which account for non-response and attrition issues generally affecting sample surveys.

The INAPP-PLUS survey is the most suitable for our purposes of studying social mobility in Italy. In fact, beyond the usual variables regarding the sociodemographic characteristics and employment conditions of individuals, it also contains information about the education level attained and the ISCO-08 rank (i.e. a classification of the complexity and range of tasks and duties to be performed in an occupation) for both interviewed people and their parents. The richness of information provided by this questionnaire therefore allows us to clearly estimate multiple effects of household background, even controlling for a number of variables related to the socioeconomic conditions of individuals.

Moreover, the INAPP-PLUS 2018 dataset contains the Ten Item Personality Inventory (TIPI) measure of the Big-5 framework, which currently enjoys considerable support and has become the most widely used model of personality (John and Srivastava 1999). Several rating instruments have been proposed to measure the Big-5 dimensions: the most comprehensive instrument is the 240-item structure developed by Costa and McCrae (1992), but the 100-item Inventory (Goldberg 1992), the 60-item Inventory (Costa and McCrae 1992), and the 44-item Big-Five Inventory (Benet-Martinez and John 1998; John and Srivastava 1999) have also been used. The TIPI, originally proposed by Gosling et al. (2003) and adapted for Italy by Chiorri et al. (2015), represents one of the simplest multi-item instruments to include in a socioeconomic survey. It assumes that individual differences in adult personality characteristics can be summarized in

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<sup>8</sup> It was shown that socio-emotional skills are significant predictors of health and health behaviours (Attanasio et al. 2020).

<sup>9</sup> The INAPP-PLUS data are available by accessing <https://inapp.org/it/dati/plus>.

<sup>10</sup> The questionnaire was distributed according to stratified random sampling of the Italian population. The stratification of the INAPP-PLUS survey sample is based on population strata by NUTS-3 region of residence, urbanization degree (i.e. metropolitan or non-metropolitan area), age group, sex, and employment status (i.e. employed, unemployed, student, retired, or other inactive status). The reference population is defined from annual averages based on the Labour Force Survey. The participants were contacted through a dynamic computer-assisted telephone interview (i.e. a CATI interview).

terms of five broad trait domains: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. Gosling et al. (2003) show that the 10-item measure reaches adequate levels in terms of: (a) convergence with widely used Big-5 measures in self-, observer, and peer reports, (b) test–retest reliability, (c) patterns of predicted external correlates, and (d) convergence between self- and observer ratings.

The analysis of the TIPI version of personality traits stems from questions on specific aspects of personality where individuals are asked to rate their perceived level on a scale from 1 to 7. For each Big-5 category there are two questions assessing the direct and the reverse aspects of each trait. In order to aggregate the two measures into a single trait, the reverse component is rescaled at the opposite (1=7; 2=6; ...; 7=1) and added to the direct component. Each trait therefore ranges from a minimum of 2 to a maximum of 14. The list of all traits and facets is reported in Table 1.

*Table 1 – The TIPI measure of the Big-5 framework*

<b>Big Five</b>	<b>Direct</b>	<b>Reverse</b>
Openness	Open to experience	Conservative
Agreeableness	Loving/Altruistic	Litigious
Conscientiousness	Self-disciplined	Careless/disorderly
Extraversion	Exuberant	Quiet/Private
Neuroticism	Anxious	Emotionally stable

In terms of possible reverse causality between personality traits and some of the outcomes in our model, the theory of the Big 5 describes these five groups of characteristics as innate attributes of individuals. Moreover, it is well accepted that personality traits are sufficiently stable across situations and one’s life course (McGue et al. 1993; Mischel and Shoda 1998; Bouchard and Loehlin 2001; McCrae and Costa 2003; 2008; Borghans et al. 2008). For these reasons, we believe that endogeneity bias (if any) should not be relevant in the estimates presented in the paper.

We applied an age restriction to the initial INAPP-PLUS 2018 sample to focus only on individuals aged 25–64. Most people aged 65 or over in Italy are retired and thus not of interest for this analysis, and most people younger than 25 are likely to still be in education. The age restriction we adopted is wider than usual (e.g. Barbieri et al. 2019 look at people aged 35–45) because we also want to explore the existence of heterogeneous effects of household background by cohort (see Section 5.3).<sup>11</sup> We also drop 1,667 observations reporting missing values in the variables of interest. Our final sample thus consists of 31,478 individuals for the analysis on educational opportunities, while it decreases to 17,899 observations when analysing social opportunities because we focus here on working individuals only.

### *3.2. Definition of variables and model specifications*

As reported by the Joint Research Centre (JRC) Technical Report (Stuhler, 2018), determining what kind of relationship should be measured when studying intergenerational mobility is not straightforward. In this analysis, we follow the approach proposed by Goldthorpe and Jackson (2008) in analysing two different dimensions together: the educational opportunities (i.e. those potentially leading to a specific socioeconomic status) and social opportunities (i.e. living standards) of individuals.

As for the first aspect, we focus on the link between parental background and the main engine of social mobility (i.e. education level). Educational opportunities can be proxied through the level of education attained, which is generally an important mediator in reaching a desired occupation, as well as the received income. Looking at the second dimension, we are instead interested in the relevance of parental background for the achievement of the current socioeconomic status of individuals. For this reason, we decided to proxy social opportunities through the occupational skill level attained according to the ISCO-08 classification, which distinguishes the following nine levels: i) managers; ii)

<sup>11</sup> One of the age groups in our analysis consists of individuals aged 36–50, a range in line with restrictions commonly adopted in the literature of intergenerational mobility. Estimations by age group, which may represent a sort of robustness check under this point of view, overall confirm that our main results hold when looking at individuals aged 36–50 only (see Section 5.3).

professionals; iii) technicians and associate professionals; iv) clerical support workers; v) services and sales workers; vi) skilled agricultural, forestry, and fishery workers; vii) craft and related trade workers; viii) plant and machine operators and assemblers; and ix) elementary occupations.<sup>12</sup>

To develop our econometric analysis on the effects of parental background, we therefore need to define two dependent variables. The first one (labelled ‘*High education level*’, or HEL) consists of a binary variable that is equal to 1 if the highest level of education attained is a university degree (0 otherwise). The second variable (labelled ‘*High skill level*’, or HSL) is defined as a dummy that is equal to 1 for employees who have reached the first three levels of the ISCO-08 classification of occupations (0 otherwise). As a sensitivity analysis, we replicated the analysis using different specifications of both dependent variables (see Section 6).

As regards the variable of interest in this analysis, household background is proxied through a variable reporting a combination of the predominant occupational skill level and the highest level of education attained by the interviewed people’s parents. In particular, using the same definitions adopted for dependent variables, we distinguish four different household backgrounds: i) parents with neither a HEL nor an HSL; ii) at least one parent with a HEL but no HSL; iii) at least one parent with an HSL but no HEL; iv) at least one parent with both a HEL and HSL.<sup>13</sup> Through this method, we are able to disaggregate the effects of educational background and social background. It must be noted that the parents’ education level and predominant occupational skill level are declared by the same interviewed people so these variables may suffer from recall bias, which is quite usual in these kinds of survey questions.

Together with the variable of interest, the Big-5 variables represent an important focus of this analysis. Each Big-5 variable is calculated as the average of two TIPI items (or descriptors), using the common stem ‘*I see myself as:*’, where each item is rated on a 7-point scale ranging from 1 (= strongly disagree) to 7 (= strongly agree).

Finally, a set of covariates is considered to control for relevant demographic and socioeconomic characteristics of individuals. Specifically, we control for gender, age group (i.e. aged less than 35, aged 36–50, aged 51 or over), size of the municipality of residence (i.e. very small, small, medium, large, and metropolitan city), macro-region of residence (i.e. North, Centre, or South) and migration status (i.e. non-migrant, domestic migrant, and foreign migrant).<sup>14</sup> A more detailed description of all variables used in the analysis, as well as their means and standard deviations, is provided in the Appendix (Table A.1).

The household background effects on educational and social opportunities of individual  $i$  are based on the probit estimation of the following model specification:

$$Y_{ij} = \beta_j HB_i + \gamma_j X_i + \delta_j BF_i + \varepsilon_{ij}, \quad j = 1, 2.$$

Here,  $Y$  is one of the  $j$  dependent variables analysed (i.e. HEL or HSL),  $HB$  represents the set of variables proxying household background (the base group is composed of people having parents with neither a HEL nor an HSL),  $X$  is a vector of covariates, and  $BF$  represents the Big-5 variables. To provide further evidence regarding each bottleneck to intergenerational mobility existing in Italy, we also estimate heterogeneous effects by macro-region, age group, migration status, and gender.

In the econometric analysis, we distinguish three different (nested) model specifications: Model 1 contains household background variables only; Model 2 adds the set of relevant covariates to Model 1; Model 3 adds Big-5 variables (i.e. openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) to Model 2.

<sup>12</sup> More details are available at <https://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm>.

<sup>13</sup> In this analysis, we refer to parents in general, without differentiating between fathers and mothers. However, some interesting gender particularities may be exploited from such precision. For the sake of simplicity, this topic will be discussed by the authors in future research.

<sup>14</sup> Other socioeconomic characteristics of individuals, such as household size, marital status, tenure status, and the household’s level of material deprivation, are not taken into account as covariates. Despite the main results (available upon request) being overall the same, we decided to exclude these variables in the presented analysis because of their potential reverse-causality issues. In addition, we excluded individual education level from the covariates, although it represents one of most important predictors of HSL and employee income, because it is too related to some occupational skill levels. For instance, a university degree is mandatory for becoming a teaching or health professional, some of the occupations included in the second level of the ISCO classification.



#### 4. Descriptive evidence

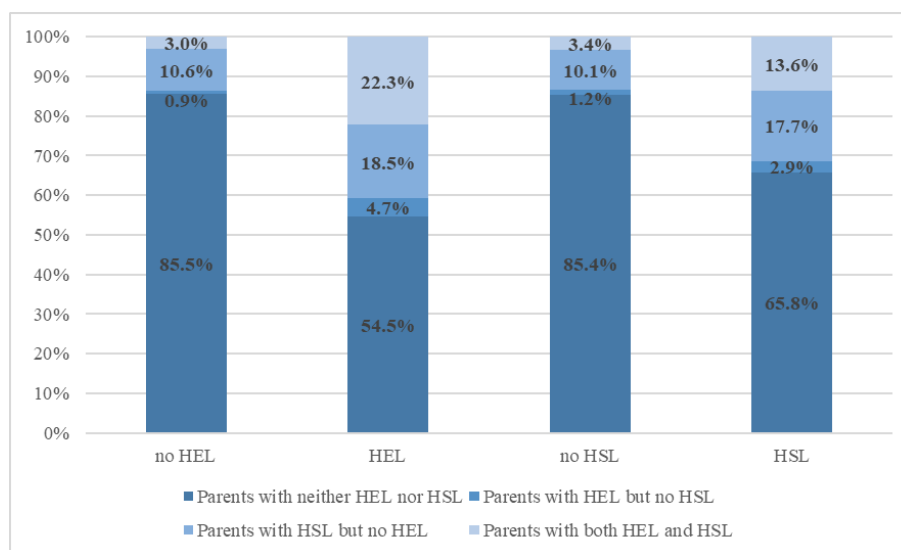
Before presenting the econometric results, we provide some preliminary evidence on the raw distribution of individuals by their education and occupational skill levels and those reported by their parents. As for education levels, Table 2 shows that in 2018, 81.3% of individuals in our sample did not attain a HEL (i.e. a university degree), and the share is even higher (91.8%) if we consider their parents. Similarly, most Italian employees (58.8%) did not reach an HSL, and their parents are characterized by an even a higher percentage (79.2%). People with at least one parent with a HEL (HSL) tend to more commonly have a HEL (HSL), but it is interesting to note that they still represent a minority among those who attained a HEL (HSL). For instance, considering 5,899 individuals reporting a HEL, only 1,593 of them come from a household with graduate parents, while the remaining 4,306 observations do not have a parent with a HEL (Table 1). This preliminary evidence seems to highlight an important increase in the level of social mobility in Italy over time. Nevertheless, it may be biased by the fact that the average level of education and occupational skills of the Italian population has increased overall in recent decades.

*Table 2 – Sample observations by HEL, HSL, and household background*

HEL attained	Parents with a HEL		Total
	No	Yes	
No	24,578	1,001	25,579
	78.1%	3.2%	81.3%
Yes	4,306	1,593	5,899
	13.7%	5.0%	18.7%
Total	28,884	2,594	31,478
	91.8%	8.2%	100.0%
HSL attained	Parents with an HSL		Total
	No	Yes	
No	9,112	1,416	10,528
	50.9%	7.9%	58.8%
Yes	5,062	2,309	7,371
	28.3%	12.9%	41.2%
Total	14,174	3,725	17,899
	79.2%	20.8%	100.0%

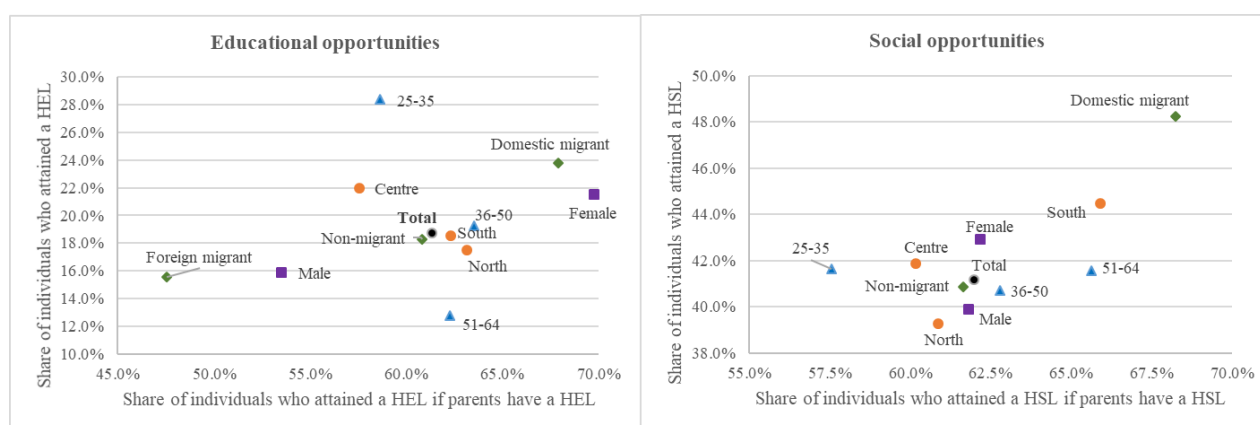
Looking at the four different types of household background defined in Section 3.1, Figure 1 confirms that parents' education and occupational skill levels matter in achieving a HEL or HSL. In fact, about 85% of individuals with no HEL (or no HSL) have parents with neither a HEL nor a HSL, while this decreases to 55% and 66% for people with a HEL or an HSL, respectively. Household background seems to have an even greater effect on the education level of individuals since even 22% of those with a HEL have parents with both a HEL and HSL. This evidence may indicate that in this bottleneck, intergenerational mobility is particularly low in Italy.

Figure 1 – Household background by individuals' education level



Looking at the heterogeneous effects among demographic, territorial, and social categories, Figure 2 points out that people aged 25–35, foreign migrants, and those residing in the centre of Italy report a ‘weaker’ relationship between household background and educational and social opportunities, on average. Therefore, these categories of the population seem to show the highest levels of intergenerational mobility. In contrast, the relevance of parental background (both in terms of educational and social opportunities) seems to be higher for domestic migrants. Individuals aged 36–50, males, and those living in northern regions present the lowest mobility in terms of educational opportunities, whereas people aged 51–64 and living in the south of Italy experience the same in terms of social opportunities.

Figure 2 – Relationship between household background and educational and social opportunities by age group, migration status, gender, and macro-region of residence



The youngest cohort of individuals shows the highest share of individuals attaining a HEL, which is evidence that the general level of education has actually increased in Italy over the last decades (Figure 2). Despite the South representing the poorest and least-developed macro-region in Italy, it is the one showing the highest share of individuals with an HSL. Although this is an unexpected preliminary result, it is likely related to a weak middle class and to the fact that the relative share of employees working in the public sector is higher in southern regions. It is also worth mentioning that domestic migrants and females present the highest shares of both HEL and HSL.

## 5. Econometric results

### 5.1. *Effects on educational and social opportunities*

Table 3 illustrates main results of the probit estimation models presented in Section 3.2 regarding the probability of attaining a HEL (first three columns) and the probability of reaching an HSL (last three columns).

The results of Models 1 and 2 for our first outcome are quietly similar: a person having parents with a HEL but no HSL report a 36–42% higher probability of obtaining a university degree (i.e. ‘high education level’) than those having parents with neither a HEL nor an HSL. The increase in the probability of attaining a HEL is even greater for individuals having parents with both a HEL and an HSL (+46–50%), while it is lower (but still significantly different from 0) when parents have a HSL but no HEL (+14–16%). As for the results regarding social opportunities, the effects of household background variables are strongly significant and positive also in this case, but differences across types of household background (and model specifications) are milder. The background ‘parents with both a HEL and HSL’ is still, however, the one with the strongest effects on the dependent variable (+38–39%). In general, having graduate parents appears more important than having parents who perform a high-skill occupation, not only for individuals’ educational careers but also for their career success.

When variables proxying the personality traits of individuals are included in the model specification (Model 3), the coefficients of the household background variables remain overall the same, but with a slight reduction. Looking at the coefficients of the Big-5 variables, Table 3 shows some differences between estimates on HEL and HSL. As for the effects on HEL, three out of the five traits seem to significantly affect the heterogeneity of the dependent variable. In particular, both openness to experience and conscientiousness have a positive effect on the probability of attaining a HEL, while agreeableness shows a negative influence. In this respect, our findings on conscientiousness are largely consistent with those of Schmidt and Hunter (2004), Chamorro-Premuzic and Furnham (2005), and Roberts et al. (2005). As regards the marginal effects on our second outcome, openness to experience and agreeableness still show a significant effect (positive and negative, respectively) on the probability of reaching an HSL. Overall, openness to experience turns out to be the Big-5 trait with the greatest influence on the probability of both academic and career success. This result is in line with those presented by Borghans et al. (2008) and Loehlin (2005). It has to be noted, however, that openness to experience is the trait with the highest intergenerational correlation (Loehlin 2005). Therefore, its effects on the analysed outcomes may be seen as further influence of household background on the educational and social opportunities of individuals.

Table 3 – Household background effects on educational and occupational skill levels: probit marginal effects

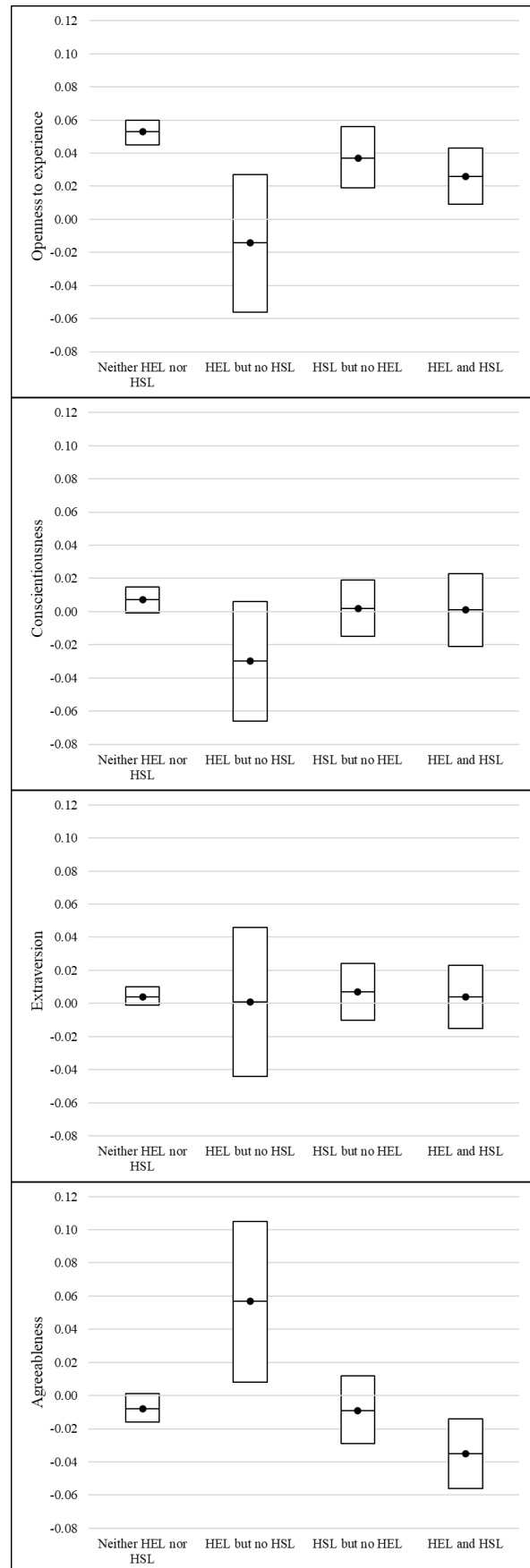
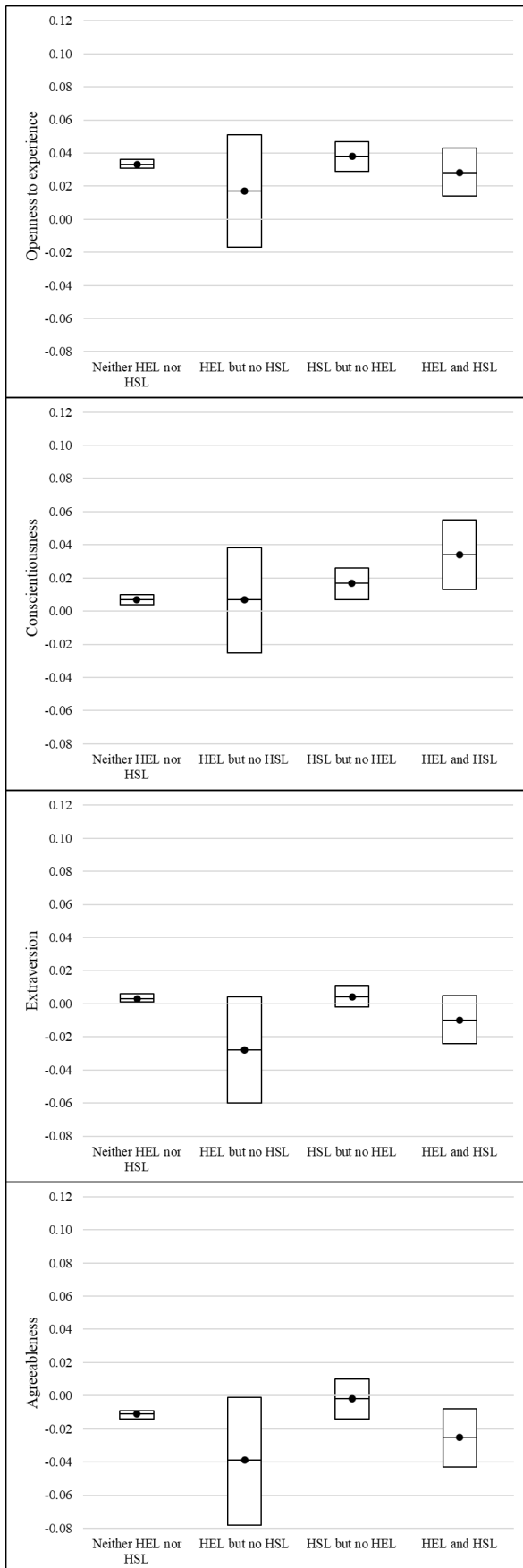
Variable	High Education Level (HEL)			High Skill Level (HSL)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Parents with a HEL but no HSL	0.417***	0.359***	0.343***	0.287***	0.286***	0.275***
<i>High education level</i>	(0.025)	(0.026)	(0.028)	<i>High skill level</i>	(0.030)	(0.032)
Parents with an HSL but no HEL	0.158***	0.141***	0.131***	0.201***	0.204***	0.195***
	(0.008)	(0.008)	(0.008)	(0.013)	(0.012)	(0.013)
Parents with both a HEL and HSL	0.502***	0.455***	0.439***	0.389***	0.380***	0.370***
	(0.013)	(0.017)	(0.016)	(0.015)	(0.015)	(0.016)
Female		0.063***	0.063***		0.028***	0.026**
		(0.005)	(0.005)		(0.010)	(0.010)
Aged 36–50		-0.053***	-0.042***		0.024	0.037**
		(0.007)	(0.007)		(0.016)	(0.017)
Aged 51–64		-0.105***	-0.088***		0.049***	0.067***
		(0.008)	(0.008)		(0.013)	(0.013)
Migrant within country		0.031*	0.028*		0.052**	0.048**
		(0.016)	(0.016)		(0.020)	(0.020)
Foreign migrant		-0.057***	-0.056***		-0.207***	-0.207***
		(0.013)	(0.015)		(0.027)	(0.028)
Small municipality		-0.001	-0.001		-0.017	-0.017
		(0.006)	(0.006)		(0.014)	(0.014)
Medium municipality		0.031***	0.029***		0.022	0.020
		(0.007)	(0.007)		(0.016)	(0.016)
Large municipality		0.042***	0.040***		0.030*	0.028*
		(0.008)	(0.008)		(0.017)	(0.017)
Metropolitan city		0.099***	0.091***		0.072***	0.063***
		(0.010)	(0.010)		(0.017)	(0.017)
Centre		0.011	0.010		-0.008	-0.010
		(0.007)	(0.007)		(0.012)	(0.012)
South		0.005	0.007		0.050***	0.049***
		(0.007)	(0.007)		(0.013)	(0.013)
Openness to experience			0.035***			0.050***
			(0.002)			(0.004)
Conscientiousness			0.010***			0.005
			(0.002)			(0.004)
Extraversion			0.002			0.005
			(0.002)			(0.003)
Agreeableness			-0.012***			-0.009*
			(0.002)			(0.005)
Neuroticism			-0.002			-0.004
			(0.001)			(0.003)
Observations	31,478	31,478	31,478	17,899	17,899	17,899

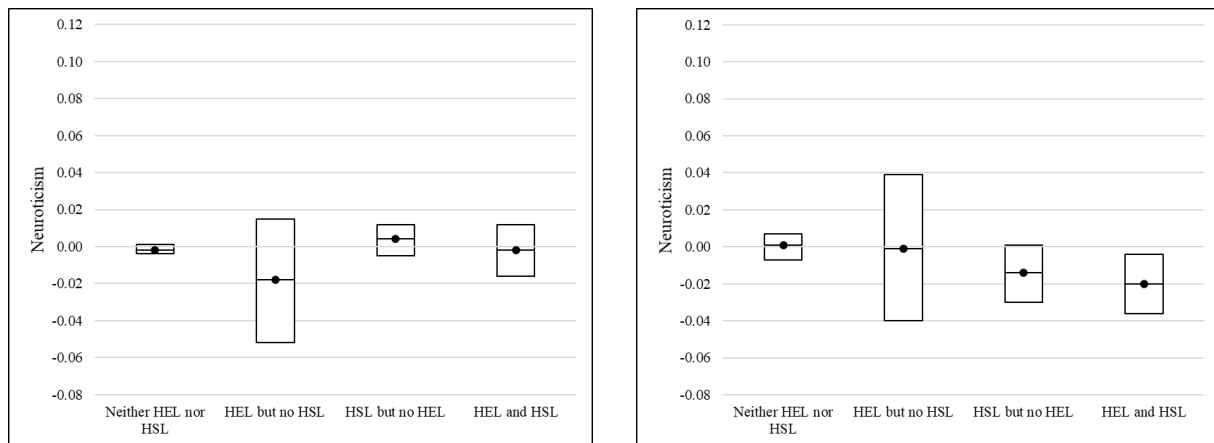
Notes: Standard errors in parentheses are clustered by province; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## 5.2. A further look at the role of the Big-5 variables

Figure 3 focuses on the relationship between the Big-5 variables and the type of household background. To this end, we add interaction terms between the Big-5 and household background variables to Model 3 (described in Section 3.2). Marginal effects of Big-5 variables presented in Figure 3 are then calculated as if everyone belongs to the same type of household background (i.e. as if everyone has parents with neither a HEL nor HSL or has parents with a HEL but no HSL, and so on).

Figure 3 – Coefficients of the interaction terms between the effect of Big-5 variables and household background variables on the educational and social opportunities of individuals: probit marginal effects





*Notes: Standard errors are clustered by province; outlined areas represent confidence intervals at the 10 percent level. Estimates are based on a Model 3 specification including interaction terms between the Big-5 and household background variables.*

It can be noted that many interaction terms are significantly different from zero (at the 10 percent level)—even some of those related to the base type of household background (i.e. ‘neither HEL nor HSL’). Specifically, the effects of openness to experience on the two outcomes appear strengthened in all household backgrounds except for the one where parents have a HEL but no HSL. The same occurs for the effects of conscientiousness, but only for the educational opportunities of individuals. In contrast, the effects of agreeableness and neuroticism (on outcomes for the former and on social opportunities for the latter) seem to be mitigated when individuals come from a background of ‘parents with both a HEL and HSL’. Interestingly, the effect of agreeableness on the probability of attaining a HEL is also mitigated in the case individuals having parents with a HEL but no HSL, while it is amplified for career success in relation to the same type of household background. Interaction terms regarding the extraversion trait are instead always statistically insignificant, except for the case of educational opportunities for those living in a household where parents have neither a HEL nor an HSL.

In conclusion, the contribution of our analysis to the literature on the Big-5 variables is threefold. First, openness to experience is by far the most important trait for both educational and labour market outcomes, while agreeableness has a negative effect on the probability of attaining a HEL or HSL. Second, the overall role of personality traits is more relevant for attaining a HEL than an HSL. Third, the effect of Big-5 variables is quite different across the observed types of household background and in some cases has an ‘equalizer’ role (with respect to the effect of household background) on the two outcomes. For instance, openness to experience partially rebalances the social opportunities of individuals since it shows a greater (positive) effect for those having parents with neither a HEL nor an HSL than those having parents with a HEL.

### 5.3. Heterogeneous effects by individual characteristics

Table 4 shows estimates of heterogeneous effects on the two analysed outcomes by age group, macro-region of residence, migration status, and the gender of individuals.

Looking at the heterogeneous effects on educational and social opportunities by age group, household background always represents an important determinant for attaining a HEL or HSL. Coefficients estimated through separate regressions by age group reveal no important differences with respect to those for the total sample of employees. Employees aged 25–35, however, show the lowest effects of household background on the probability of attaining a HEL (except for the type ‘parents with an HSL but no HEL’). This finding seems to suggest that household background is less relevant for the educational opportunities of individuals in the younger cohorts, but it may also reflect the greater preference for university enrolment observed in Italy after the Great Recession (Bonacini, 2020).

Table 4 – Household background effects on educational and occupational skill levels by individual characteristics: probit marginal effects

Dependent variable	Variable of interest	Total	Aged 25–35	Aged 36–50	Aged 51–64	North	Centre	South	Non-migrant	Domestic migrant	Foreign migrant	Male	Female
High Education Level (HEL)	Parents with a HEL but no HSL	0.343*** (0.028)	0.323*** (0.030)	0.343*** (0.045)	0.501*** (0.061)	0.346*** (0.040)	0.272*** (0.022)	0.406*** (0.049)	0.353*** (0.028)	0.330*** (0.090)	0.213** (0.093)	0.311*** (0.034)	0.374*** (0.038)
	Parents with an HSL but no HEL	0.131*** (0.008)	0.133*** (0.017)	0.123*** (0.011)	0.141*** (0.014)	0.126*** (0.010)	0.121*** (0.019)	0.140*** (0.014)	0.130*** (0.008)	0.139*** (0.031)	0.093** (0.040)	0.109*** (0.011)	0.153*** (0.012)
	Parents with both a HEL and HSL	0.439*** (0.016)	0.390*** (0.020)	0.494*** (0.023)	0.451*** (0.030)	0.458*** (0.018)	0.377*** (0.022)	0.461*** (0.017)	0.435*** (0.016)	0.462*** (0.044)	0.468*** (0.093)	0.394*** (0.022)	0.486*** (0.017)
	Observations	31,478	7,532	11,295	12,651	14,464	6,406	10,608	28,020	2,877	581	13,495	17,983
Dependent variable	Variable of interest	Total	Aged 25–35	Aged 36–50	Aged 51–64	North	Centre	South	Non-migrant	Domestic migrant	Foreign migrant	Male	Female
High Skill Level (HSL)	Parents with a HEL but no HSL	0.275*** (0.033)	0.288*** (0.051)	0.263*** (0.044)	0.284*** (0.065)	0.249*** (0.049)	0.186*** (0.043)	0.432*** (0.042)	0.283*** (0.038)	0.267*** (0.061)	0.163 (0.107)	0.295*** (0.044)	0.253*** (0.036)
	Parents with an HSL but no HEL	0.195*** (0.013)	0.142*** (0.026)	0.217*** (0.024)	0.197*** (0.019)	0.202*** (0.017)	0.162*** (0.028)	0.206*** (0.027)	0.193*** (0.014)	0.186*** (0.037)	0.218*** (0.084)	0.210*** (0.020)	0.177*** (0.016)
	Parents with both a HEL and HSL	0.370*** (0.016)	0.365*** (0.030)	0.361*** (0.027)	0.386*** (0.021)	0.383*** (0.018)	0.320*** (0.021)	0.391*** (0.035)	0.381*** (0.018)	0.288*** (0.055)	0.305*** (0.099)	0.386*** (0.025)	0.350*** (0.016)
	Observations	17,899	4255	6,710	6,934	9,235	3,890	4,774	15,854	1,741	304	8,559	9,340

Notes: Standard errors in parentheses are clustered by province; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Estimated models also include all other covariates in Model 3.

As for the results by macro-region of residence, individuals living in the southern regions of Italy always report the highest effects of household background on the two outcomes, followed by those living in the northern areas. The estimated coefficients reported by the two categories of employee are not significantly different from each other except for the effect of the background ‘parents with a HEL but no HSL’ on the probability of attaining an HSL. In contrast, individuals living in the central regions of Italy tend to be characterised by a lower influence (significant at the 5 percent level in most cases) of household background on the analysed outcomes. Unexpectedly, we also note that the estimated coefficients related to the background ‘parents with both a HEL and HSL’ are not always the highest in this case. In fact, when looking at the effects on the HSL among employees living in the South, having parents with a HEL but no HSL engenders a greater effect on the dependent variable (+43% probability of attaining a HSL occupation) than having parents with a HEL and HSL (+39%).

As regards the sample disaggregation by migrant status, the results show that also in this case, the effects of household background on the two outcomes are quite similar across the groups of individuals. Nonetheless, foreign migrants report smaller or insignificant effects on educational and social opportunities for the background ‘parents with a HEL but no HSL’. Interesting findings arise instead when distinguishing by the gender of individuals. Estimated coefficients of the household background variables on educational opportunities are always higher among females, suggesting a greater importance of the family for women in order to attain a university degree. Conversely, when looking at the effects on social opportunities, we find higher coefficients among males (differences in coefficients between the two groups are never statistically significant, however). Therefore, household background appears to matter more for females as a means to obtain educational success, but after that milestone, it becomes more relevant for males in order to have success in the workplace.

In conclusion, this analysis of heterogeneous effects by demographic characteristics of individuals highlights that the effects of household background on educational and social opportunities are pretty robust across the Italian population, showing slight differences between the observed categories. On the one hand, this evidence seems to exclude the case of further unequal conditions of access to tertiary education or to high-skill occupations for specific categories of the population. On the other one hand, however, our findings emphasize the extent of the phenomenon of intergenerational immobility in Italy, as nobody seems to be exempt from the relevant role of household background in educational and job success.

To go further in depth into the effects of the Big-5 variables on the analysed outcomes, Table 5 illustrates the estimated coefficients of personality trait variables by individual characteristics. The results of Wald F-tests on the joint significance of Big-5 variables confirm that personality traits are important predictors of educational and social opportunities of individuals throughout the population, but their (joint) relevance seems smaller among non-native and younger individuals. Moreover, Table 5 clearly shows that the significant influence of openness to experience on the probability of attaining a HEL or an HSL regards all individuals/employees, regardless of their demographic characteristics.

Looking at the effects on educational opportunities, the conscientiousness and agreeableness traits seem not to have any effect on the dependent variable for non-native individuals only (the conscientiousness coefficient is also insignificant among those aged 51–64). Although its effect is statistically insignificant for the total sample, extraversion engenders a higher probability of obtaining a university degree among females, individuals aged 51–64, and those living in southern regions, while it presents an opposite (but significant) effect among those living in the North. Interestingly, neuroticism has no significant effect for the total sample of individuals, probably because its effect is opposite for females and males. Specifically, a greater level of neuroticism determines a higher probability of attaining a HEL for males and a lower one for females (and for people aged 51–64 or living in the Centre of Italy).

With the exception of openness to experience, the effects of the Big-5 variables appear insignificant overall when looking at the estimates on HSL (Table 5). It can be noted that the negative effect of agreeableness observed for the total sample is mainly due to its significant effect among people aged 51–64, those living in the central regions, and native (i.e. non-migrant) individuals. As for the other personality traits, the effect of conscientiousness is significant among young employees only, and extraversion among those aged 51–64, and neuroticism has a positive effect for foreign migrants and a negative one for females.



Table 5 – Effects of the Big-5 variables on educational and occupational skill level by individual characteristics: probit marginal effects

Dependent variable	Variable of interest	Total	Aged 25–35	Aged 36–50	Aged 51–64	North	Centre	South	Non-migrant	Domestic migrant	Foreign migrant	Male	Female
High Education Level (HEL)	Openness to experience	0.035*** (0.002)	0.032*** (0.005)	0.041*** (0.003)	0.028*** (0.002)	0.035*** (0.002)	0.039*** (0.003)	0.033*** (0.003)	0.034*** (0.002)	0.046*** (0.007)	0.029*** (0.010)	0.027*** (0.002)	0.043*** (0.002)
	Conscientiousness	0.010*** (0.002)	0.016*** (0.005)	0.014*** (0.003)	0.003 (0.002)	0.009*** (0.003)	0.013*** (0.003)	0.010*** (0.003)	0.011*** (0.002)	0.004 (0.008)	0.006 (0.010)	0.010*** (0.002)	0.011*** (0.002)
	Extraversion	0.002 (0.002)	-0.002 (0.004)	0.001 (0.003)	0.005*** (0.002)	-0.005** (0.002)	0.001 (0.004)	0.011*** (0.002)	0.001 (0.002)	0.010 (0.006)	0.005 (0.008)	-0.002 (0.002)	0.005** (0.002)
	Agreeableness	-0.012*** (0.002)	-0.013** (0.006)	-0.013*** (0.003)	-0.010*** (0.002)	-0.012*** (0.003)	-0.015*** (0.004)	-0.012*** (0.003)	-0.013*** (0.002)	-0.004 (0.009)	-0.013 (0.011)	-0.008*** (0.003)	-0.015*** (0.003)
	Neuroticism	-0.002 (0.001)	-0.002 (0.004)	0.001 (0.003)	-0.004** (0.002)	0.000 (0.002)	-0.008** (0.003)	-0.001 (0.003)	-0.002 (0.001)	0.000 (0.004)	-0.003 (0.009)	0.007*** (0.002)	-0.010*** (0.002)
	Observations	31,478	7,532	11,295	12,651	14,464	6,406	10,608	28,020	2,877	581	13,495	17,983
	F test (Big-5 variables)	602.9***	66.7***	244.7***	315.4***	241.5***	435.2***	270.2***	461.4***	53.4***	11.9**	234.4***	448.1***
Dependent variable	Variable of interest	Total	Aged 25–35	Aged 36–50	Aged 51–64	North	Centre	South	Non-migrant	Domestic migrant	Foreign migrant	Male	Female
High Skill Level (HSL)	Openness to experience	0.050*** (0.004)	0.037*** (0.009)	0.049*** (0.007)	0.058*** (0.006)	0.047*** (0.006)	0.054*** (0.006)	0.051*** (0.007)	0.051*** (0.004)	0.041*** (0.014)	0.043** (0.020)	0.055*** (0.006)	0.042*** (0.005)
	Conscientiousness	0.005 (0.004)	0.022** (0.010)	-0.003 (0.007)	0.008 (0.006)	0.008 (0.007)	0.002 (0.008)	0.003 (0.008)	0.005 (0.005)	0.005 (0.015)	0.020 (0.019)	0.005 (0.006)	0.006 (0.006)
	Extraversion	0.005 (0.003)	-0.004 (0.007)	0.012*** (0.005)	0.002 (0.005)	0.003 (0.004)	0.006 (0.006)	0.009 (0.006)	0.004 (0.003)	0.014 (0.012)	0.003 (0.019)	0.006 (0.005)	0.004 (0.004)
	Agreeableness	-0.009* (0.005)	-0.010 (0.010)	-0.005 (0.007)	-0.013** (0.007)	-0.009 (0.006)	-0.016* (0.008)	-0.003 (0.009)	-0.009* (0.005)	0.001 (0.016)	-0.016 (0.020)	-0.009 (0.006)	-0.008 (0.006)
	Neuroticism	-0.004 (0.003)	-0.004 (0.008)	-0.008 (0.006)	0.003 (0.005)	-0.004 (0.005)	-0.007 (0.008)	-0.001 (0.006)	-0.006 (0.004)	0.008 (0.011)	0.033* (0.020)	0.003 (0.005)	-0.012*** (0.004)
	Observations	17,899	4,255	6,710	6,934	9,235	3,890	4,774	15,854	1,741	304	8,559	9,340
	F test (Big-5 variables)	192.2***	25.9***	71.5***	94.23***	78.6***	139.5***	57.8***	162.7***	10.6*	13.9**	80.8***	92.6***

Notes: Standard errors in parentheses are clustered by province; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Estimated models also include all other covariates in Model 3.

## 6. Robustness checks

In this section, we present some robustness checks on the main results highlighted in the paper, namely concerning the specification of the variable of interest, the specification of the dependent variable, and the inclusion of further (potentially endogenous) covariates in the model specification.

First, we replaced the specification of household background variables (i.e. our variables of interest) from those described in Section 3.2 to a new one where parental education and occupation skill level are included through by-level variables. In particular, we include two dummy variables for parental education level ('parents with a high school diploma' and 'parents with a university degree', while individuals having parents with no diploma represent the base group) and six dummy variables for parental occupation skill level (the base group is composed of individuals having at least one parent who performed an occupation with an ISCO-08 level equal to 1). (We use six dummy variables representing parental occupation skill level rather than eight, due to few observations.) Table A.2 reports the results of this robustness check for the HEL and HSL estimations.

Individuals having parents (at least one) with a diploma are more likely to attain a HEL or an HSL than those having parents with no diploma, but as expected, having parents with a university degree has an even greater effect on the two outcomes. As regards the household background variables related to the occupational skill level of parents, individuals having parents (at least one) who performed an occupation with an ISCO level equal to 1 have the same probability of attaining a HEL than those having parents who have reached (at maximum) an ISCO level equal to 4, and a lower one than those having parents with an ISCO occupational level of 2 or 3. In all other cases (i.e. individuals having parents who perform an occupation with a skill level equal to ISCO 5 or higher), the coefficients are instead negative. The latter evidence appears even worse in terms of intergenerational mobility if we consider estimates on HSL, since in this case effects are negative starting from individuals with parents who reached an ISCO level equal to 4 (Table A.2).

Since we define dependent variables in the main analysis as dummies to reduce their variability and thus improve estimation efficiency, as a second robustness check we verified that our results hold when changing their specification. In particular, we replicated our main analysis considering as dependent variables the following discrete ordered variables: a 3-level variable for individuals' education (i.e. lower-secondary education, upper-secondary education, and tertiary education) and an 8-level variable for individuals' occupation skill (i.e. one level per ISCO rank). (Individuals performing an occupation belonging to ISCO levels 6 and 7 are considered together due to few observations.) Based on ordered probit estimation models, the results of this robustness check strongly corroborate the main considerations coming out of our analysis (Table A.3). Three findings are worth mentioning here, however. First, having parents with a HEL (independently from also having an HSL) decreases the probability of attaining an educational level lower than tertiary, while parents with an HSL but no HEL significantly drive their children to obtain a high school diploma as well (with respect to those with neither a HEL nor an HSL). Second, these results regarding the social opportunities of individuals highlight very clearly the existence in Italy of a 'glass ceiling'—strictly related to household background—between people in the high occupational skill levels (and almost, consequently, in the upper classes) and those in the low ones. In fact, any kind of household background different from 'parents with neither a HEL nor HSL' engenders a higher probability of reaching the first three ISCO levels and a lower probability of falling into the higher levels of occupational skill. Third, openness to experience, conscientiousness, and extraversion tend to push individuals to attain high education levels and to perform high-skilled occupations, while the opposite occurs for agreeableness.

Finally, we tried to include further (potentially endogenous) covariates in the model specification. With reference to the estimations on HSL (i.e. those considering working individuals only), Model 4 adds the following job-related variables to Model 3: economic sector (i.e. agriculture, industry, and services), employment status (i.e. full-time open-ended worker, part-time open-ended worker, self-employed, and temporary worker or other status), a dummy equal to 1 for those working in the public sector, and the perceived job mismatch (both in terms of formal education and skills). More details on these new covariates can be found in Table A.1. The results of this third robustness check, illustrated in Table A.4, show that the effects of household background on the two analysed outcomes, decrease in magnitude but remain overall the same when including these additional covariates.

## 7. Conclusions

The petrification of social classes across generations is currently a widespread phenomenon: recent simulations on earnings persistence elasticities suggest that the children of poorer families need almost five generations to reach the average income in several OECD countries (OECD 2018b). Focusing on the Italian case, our paper represents a possible starting point to build targeted policy proposals aimed at moving towards a less class-based society, as it intends to determine the relevance of parental background through a multidimensional point of view and explores the moderating role of personality traits accounting for some social and demographic differences.

Based on data from the INAPP-PLUS 2018 survey, preliminary results on the relationship between household background (i.e. parental education and occupational skill level) and variables representing the educational and social opportunities of individuals (i.e. having a HEL and having an HSL) show that parental background clearly matters in Italy: people having parents with a HEL or HSL (or both) tend to more frequently attain a HEL or HSL, indicating that the ‘petrification’ of Italian society as a whole is relevant in terms of both educational and social opportunities.

The econometric results overall confirm that household background has a strong and significant effect on both of the analysed outcomes, even when controlling for a set of relevant demographic and socioeconomic characteristics of individuals. In particular, we point out that having graduate parents seems to be more important than having parents who perform a high-skill occupation, not only for individuals’ educational careers but also for their job-career success.

The inclusion of Big-5 variables in the model helps control for omitted variables and reduces the unobserved heterogeneity in intergenerational social mobility among individuals with the same level of education and skills. Nevertheless, through an interaction-term analysis we are able to point out that the effects of the personality traits are quite heterogeneous across the observed types of household background, and openness to experience is the most important trait for both educational and labour market outcomes. Personality traits are therefore able to influence the link between household background and individuals’ outcomes, thus exercising an ‘equalizer’ role (with respect to the effect of household background) in some cases. More specifically, individuals with a high level of openness to experience are able to partially rebalance the lack of education and skills of their parents since this personality trait has a greater (positive) effect for those having parents with neither a HEL nor an HSL than those having parents with a HEL.

The disaggregation by demographic and social characteristics points out that the influence of parental background is slightly more prevalent in the southern regions and interestingly, there appears to be a greater importance of the family for women in order to attain a university degree, whereas this is more important for men in terms of social opportunities. It is significant that in country like Italy, with a persisting north-south dualism (Daniele and Malanima 2013, Ricci and Scicchitano, 2021), the area with the lowest rate of employment also tends to show the highest correlation between the parental background and individuals’ social opportunities. Our main findings therefore confirm that the Italian labour market is both dual and unequal, especially from a generational standpoint (Garibaldi and Taddei 2013).

In conclusion, our study highlights that parental education and occupational skill levels have different effects on the living standards of their children, with the former appearing to be more relevant than the latter. From this evidence, it is possible to state that issues regarding intergenerational mobility in the analysed country are stratified over more interconnected layers different from each other. A deeper understanding of equal-opportunity mechanisms is necessary in order to promote public policies able to stimulate social mobility. The most important political implication of our results involves the definition of policies promoting—in an economic and especially in a cultural way—tertiary education for youths coming from non-graduate (and often poorer) households. These policies should be more focused on Southern Italy, where the family background is found to be more relevant. Moreover, individual characteristics should be taken into consideration: in particular, policies applied in the education system have to consider the particular context of women. This could take the form of, for example, income support aimed at supporting young women from lower socioeconomic backgrounds during their university careers. Reaching true equality of opportunities is an urgent issue for a modern country. The more one’s progression path depends solely on effort, the more social justice will prevail in our society.

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## Appendix

Table A.1 – Variable descriptions

Variables	Description	Obs.	Mean	Std. Dev.
Dependent variables				
High education level (HEL)	Binary variable equal to 1 if the highest education level attained is a university degree and 0 otherwise.	31,478	0.187	0.390
High skill level (HSL)	Binary variable equal to 1 for employees reaching the first three levels of the ISCO classification of occupations (i.e. managers, professionals, technicians and associate professionals) and 0 otherwise.	17,899	0.412	0.492
Variables of interest				
Parents with a HEL but no HSL	Binary variables representing household background. Parents have a high education level if at least one of them obtained a university degree. Similarly, parents have a high occupational skill level if at least one of them reached the first three levels of the ISCO classification of occupations. The reference category is parents with neither a HEL nor an HSL.	31,478	0.016	0.126
Parents with an HSL but no HEL		31,478	0.121	0.326
Parents with both a HEL and HSL		31,478	0.066	0.249
Control variables				
Openness to experience	Discrete variables representing the Big Five personality traits of individuals. A complete description of these variables is provided in Section 3.2.	31,478	4.298	1.218
Conscientiousness		31,478	5.809	1.164
Extraversion		31,478	3.690	1.451
Agreeableness		31,478	5.499	1.158
Neuroticism		31,478	3.010	1.385
Female	Binary variable taking a value of 1 for females and 0 for males.	31,478	0.509	0.500
Aged 36–50	Binary variables representing the age group of individuals. The reference category is ‘aged 25–35’.	31,478	0.428	0.495
Aged 51–64		31,478	0.367	0.482
Small municipality	Binary variables representing the size of the municipality of residence. A small municipality has a number of inhabitants between 5,000 and 20,000, a medium municipality has 20,000–50,000 inhabitants, a large municipality counts 50,000–50,000 inhabitants, and a metropolitan city has 250,000 or more inhabitants. The reference category is ‘very small municipality’ (number of inhabitants lower than 5,000).	31,478	0.319	0.466
Medium municipality		31,478	0.164	0.371
Large municipality		31,478	0.173	0.378
Metropolitan city		31,478	0.132	0.338
Centre	Binary variables representing the macro-region of residence. The reference category is ‘North’.	31,478	0.197	0.397
South		31,478	0.342	0.475
Migrant within macro-region	Binary variables representing migration status. An individual is a ‘migrant within macro-region’ if her region of birth and her region of residence belong to the same macro-region (i.e. North, Centre, or South). An individual is a ‘migrant within country’ if her region of birth belongs to a different macro-region with respect to her region of residence. An individual is a ‘foreign migrant’ if she moves from outside of Italy. The reference category is ‘local’.	31,478	0.029	0.168
Migrant within country		31,478	0.062	0.241
Foreign migrant		31,478	0.020	0.138
Industry	Binary variables representing the sector of activity for employees. The services sector is split into four categories according to the purpose. The reference category is ‘agriculture’.	17,899	0.218	0.413
Services		17,899	0.739	0.439
Part-time open-ended worker	Binary variables representing the type of employment contract. The reference category is ‘full-time open-ended worker’.	17,899	0.121	0.327
Self-employed		17,899	0.207	0.405
Temporary worker and other		17,899	0.121	0.326
Public sector	Binary variable taking a value of 1 for employees working in the public sector and 0 otherwise.	17,899	0.240	0.427
Formal educational mismatch	Binary variable equal to 1 for employees who consider their education level necessary to do their actual job and 0 otherwise.	15,799	0.297	0.457
Skills mismatch	Binary variable taking a value of 1 for employees who consider their skills to be in line with those requested to do their actual job and 0 otherwise.	15,799	0.413	0.492

Table A.2 – Household background effects (through by-level variables) on the educational and social opportunities of individuals: probit marginal effects

VARIABLES	High Education Level (HEL)		High Skill Level (HSL)	
	Model 2	Model 3	Model 2	Model 3
Parents with diploma	0.140*** (0.007)	0.132*** (0.007)	0.140*** (0.016)	0.132*** (0.017)
Parents with university degree	0.369*** (0.017)	0.357*** (0.017)	0.285*** (0.023)	0.276*** (0.024)
Parents' highest skill level = 2 or 3	0.029*** (0.011)	0.030*** (0.011)	-0.008 (0.020)	-0.006 (0.020)
Parents' highest skill level = 4	0.000 (0.010)	0.002 (0.010)	-0.086*** (0.019)	-0.083*** (0.020)
Parents' highest skill level = 5	-0.031** (0.012)	-0.028** (0.011)	-0.099*** (0.027)	-0.096*** (0.027)
Parents' highest skill level = 6 or 7	-0.103*** (0.009)	-0.096*** (0.009)	-0.199*** (0.021)	-0.190*** (0.022)
Parents' highest skill level = 8	-0.115*** (0.010)	-0.109*** (0.010)	-0.197*** (0.024)	-0.189*** (0.024)
Parents' highest skill level = 9	-0.130*** (0.010)	-0.122*** (0.009)	-0.209*** (0.035)	-0.199*** (0.034)
Openness to experience		0.029*** (0.001)		0.044*** (0.004)
Conscientiousness		0.009*** (0.002)		0.005 (0.004)
Extraversion		0.000 (0.002)		0.004 (0.003)
Agreeableness		-0.011*** (0.002)		-0.008* (0.005)
Neuroticism		-0.001 (0.001)		-0.004 (0.003)
Observations	31,478	31,478	17,899	17,899

Notes: Standard errors are clustered by province; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Estimated models also include all other covariates in Models 2 and 3. The base level of parental education level is 'parents not having a diploma', the base level of parental occupation skill level is 'parents' highest skill level = 1'.

Table A.3 – Household background and Big-5 effects on the educational and occupational skill level of individuals: ordered probit marginal effects

Variables	Y = Probability of having a(n) ...										
	Lower- secondary educ. level	Upper- secondary educ. level	Tertiary educ. level	O.S.L. = 1	O.S.L. = 2	O.S.L. = 3	O.S.L. = 4	O.S.L. = 5	O.S.L. = 6-7	O.S.L. = 8	O.S.L. = 9
Parents with a HEL but no HSL	-0.336*** (0.015)	-0.018 (0.016)	0.354*** (0.030)	0.080*** (0.012)	0.140*** (0.013)	0.034*** (0.002)	-0.024*** (0.005)	-0.051*** (0.006)	-0.081*** (0.008)	-0.042*** (0.004)	-0.057*** (0.004)
Parents with an HSL but no HEL	-0.195*** (0.009)	0.053*** (0.003)	0.142*** (0.009)	0.043*** (0.004)	0.092*** (0.007)	0.031*** (0.002)	-0.007*** (0.002)	-0.030*** (0.003)	-0.055*** (0.005)	-0.030*** (0.002)	-0.044*** (0.003)
Parents with both a HEL and HSL	-0.371*** (0.010)	-0.073*** (0.013)	0.444*** (0.020)	0.115*** (0.006)	0.171*** (0.008)	0.031*** (0.002)	-0.040*** (0.004)	-0.066*** (0.004)	-0.099*** (0.005)	-0.048*** (0.003)	-0.063*** (0.003)
Openness to experience	-0.060*** (0.003)	0.022*** (0.001)	0.038*** (0.002)	0.009*** (0.001)	0.023*** (0.003)	0.009*** (0.001)	-0.000 (0.000)	-0.007*** (0.001)	-0.014*** (0.001)	-0.008*** (0.001)	-0.012*** (0.001)
Conscientiousness	-0.024*** (0.003)	0.009*** (0.001)	0.015*** (0.002)	0.002** (0.001)	0.006** (0.002)	0.002** (0.001)	-0.000 (0.000)	-0.002*** (0.001)	-0.003** (0.001)	-0.002** (0.001)	-0.003** (0.001)
Extraversion	-0.008*** (0.003)	0.003*** (0.001)	0.005*** (0.002)	0.001** (0.001)	0.004** (0.002)	0.001** (0.001)	-0.000 (0.000)	-0.001** (0.000)	-0.002** (0.001)	-0.001** (0.001)	-0.002** (0.001)
Agreeableness	0.022*** (0.003)	-0.008*** (0.001)	-0.014*** (0.002)	-0.003*** (0.001)	-0.007*** (0.002)	-0.003*** (0.001)	0.000 (0.000)	0.002*** (0.001)	0.004*** (0.001)	0.003*** (0.001)	0.004*** (0.001)
Neuroticism	0.005** (0.002)	-0.002** (0.001)	-0.003** (0.001)	0.000 (0.001)	0.000 (0.002)	0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Observations	31,478	31,478	31,478	17,899	17,899	17,899	17,899	17,899	17,899	17,899	17,899

Notes: Standard errors are clustered by province; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Estimated models also include all other covariates in Model 3. The base group is composed of individuals having parents with neither a HEL nor an HSL.

Table A.4 – Household background effects on the educational and occupational skill level of individuals (additional covariates): probit marginal effects

Variable	High Skill Level (HSL)		
	Model 3	Model 4	Model 5
Parents with a HEL but no HSL	0.275***	0.257***	0.169***
Parents with an HSL but no HEL	0.195***	0.163***	0.125***
Parents with both a HEL and HSL	0.370***	0.332***	0.231***
Female	0.026**	0.034***	-0.009
Aged 36–50	0.037**	-0.013	0.011
Aged 51–64	0.067***	-0.030**	0.018
Domestic migrant	0.048**	0.048**	0.066***
Foreign migrant	-0.207***	-0.183***	-0.116***
Small municipality	-0.017	-0.008	-0.020
Medium municipality	0.020	0.022	0.005
Big municipality	0.028*	0.025	0.005
Metropolitan city	0.063***	0.048***	0.027**
Centre	-0.010	-0.021*	-0.046***
South	0.049***	0.001	-0.016
Openness to experience	0.050***	0.045***	0.037***
Conscientiousness	0.005	0.008*	-0.004
Extraversion	0.005	0.003	0.005*
Agreeableness	-0.009*	-0.008*	0.002
Neuroticism	-0.004	-0.002	-0.004
Industry		0.059**	0.117***
Services		0.164***	0.183***
Part-time open-ended worker		-0.170***	-0.176***
Self-employed		0.278***	0.300***
Temporary worker and other		-0.108***	-0.050***
Public sector		0.266***	0.214***
Formal education mismatch			-0.274***
Skills mismatch			-0.008
Observations	17,899	17,899	15,799

Notes: Standard errors in parentheses are clustered by province; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .