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Abstract

This paper investigates the relationship between intergenerational inequality and differences in pay policies among firms. We examine whether the effects of parental background in firm selection contribute to the persistence of income inequality across generations, and particularly how this can enhance the understanding of transmission mechanisms beyond the traditional role of education. We first apply a two-way fixed-effects wage estimation, a' la AKM, to the Italian private sector. Our results indicate that the allocation of workers to firms with different wage policies is significantly influenced by the economic background of their parents. This influence on wages is significant and relatively greater than the impact of individual worker characteristics. Furthermore, the background effect amplifies from initial jobs to job changes and negatively affects the sorting between firm and worker types.

Keywords: Firm effect; Intergenerational inequality; Labor market; Unobservable abilities; Wage inequality.
JEL: I24, J21, J24, J31.

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Premi salariali di background, oltre l'istruzione: selezione nelle imprese e abilità non osservabili

Sommario

Questo articolo indaga la relazione tra disuguaglianza intergenerazionale e le differenze nelle politiche retributive tra le imprese. Esaminiamo se gli effetti del background familiare nella selezione delle imprese contribuiscano alla persistenza della disuguaglianza di reddito tra generazioni, e in particolare come ciò possa ampliare la comprensione dei meccanismi di trasmissione oltre il ruolo tradizionale dell'istruzione. Applichiamo innanzitutto una stima salariale con stima two-way fixed-effects, alla AKM, al settore privato italiano. I nostri risultati indicano che l'allocazione dei lavoratori alle imprese con diverse politiche salariali è significativamente influenzata dalla condizione economica dei genitori. Questa influenza sui salari è significativa e relativamente più forte rispetto all'impatto delle caratteristiche individuali del lavoratore. Inoltre, l'effetto del background si amplifica dal primo impiego ai successivi cambi di lavoro e influisce negativamente sul processo di assortimento tra le tipologie di imprese e di lavoratori.

Parole chiave: Effetto impresa; Disuguaglianza intergenerazionale; Mercato del lavoro; Abilità non osservabili; Disuguaglianza salariale.
JEL: D22, J08, J21.

1 Introduction

Recent research has shown that a substantial portion of wage inequalities can be attributed to differences between firms rather than differences among individuals within firms (Abowd et al., 1999; Card et al., 2013). Firm fixed effects capture the impact of firm-specific characteristics on wages, including market power, profitability, human capital investments, technology adoption, and industry affiliation. This component of inequality played a crucial role in the increase in inequalities experienced in Western economies (Autor et al., 2008; Barth et al., 2016). Recent papers have also explored specific dimensions of inequality, as for the case of gender gaps (Casarico and Lattanzio, 2024). In this paper, we aim to test the extent to which firm premia can help explain also the intergenerational dimension of inequality. In particular, we focus on graduates as to contribute to the literature on the channels that parental background exerts beyond the traditional one related to education.

Indeed, even after controlling for educational attainment, the literature on intergenerational inequalities in the labor market consistently evidences substantial wage premia associated with family background (Lam and Schoeni, 1993). This crucial for its indirect effect on educational enrollment, as differing returns to education by family background may further discourage disadvantaged groups from pursuing higher education, reinforcing segregation. The exploration of these further transmission factors lies at the intersection of sociological and economic aspects (Bowles et al., 2009). From the economics perspective, Agnarsson and Carlin (2002) have pointed out the fact that education is only one part of the formation of individual productive capacities. Accordingly, the residual background premium is ascribed to individual features that are not proxied by education and thus empirically correspond to unobserved abilities. These unobservable factors may include inherent skills, cultural capital, or other socio-cognitive attributes inherited or nurtured by family environments. These factors continue to influence economic outcomes despite equivalent levels of formal education. More recent empirical research has instead focused on further channels beyond mere education and inherent abilities through which family background may influence economic outcomes. This points out the embedded nature of labor market relationships and thus shifts the attention to more sociological aspects (Granovetter, 1973, 1983). This body of work has identified several mechanisms, including job referrals, nepotism, social ties, and the direct transmission of employers from one generation to the next (Corak and Piraino, 2011; Hudson and Sessions, 2011; Raitano and Vona, 2018). These channels often provide access to job opportunities and career advancements that are not available through formal education alone. For example, job referrals and social networks can offer crucial advantages by providing inside information about job openings or influencing hiring decisions, which can lead to better job matches and higher wages. Nepotism can result in preferential treatment within hiring processes, while direct transmission of employers can ensure job security and career continuity within families. These practices often embed economic relationships within social frameworks, allowing family members to benefit from the connections and reputation built by previous generations.

Some researchers argue that such mechanisms can be seen as efficient responses to market imperfections (Magruder, 2010; Bavaro and Patriarca, 2022). In this view, economic relationships are deeply embedded in social contexts, enabling quicker and more reliable exchanges of information and trust within established networks. This perspective suggests that these channels might serve practical functions in overcoming informational asymmetries and transaction costs in the labor market. However, others contend that these mechanisms often reflect rent-seeking behaviors, where individuals and families leverage their social and economic capital to secure economic rents, leading to persistent inequalities and reduced social mobility (Mocetti, 2016; Franzini et al., 2020). This rent-seeking perspective highlights how these practices can entrench existing advantages, allowing certain families to maintain economic dominance across generations, irrespective of individual merit or educational attainment (Mocetti et al., 2022; Raitano and Vona, 2021).

In this paper we employ the wage decomposition approach developed by Abowd et al. (1999, AKM henceforth) to disentangle and identify two different aspects of intergenerational transmission. As mentioned before, the first category includes channels that act on individual-specific characteristics, commonly referred to as unobservable abilities. The second category focuses on channels that affect the allocation of workers to firms with varying wage policies, thereby influencing whether employees end up in firms with more or less favorable compensation structures. Such between firms' wage differentials emerge as a result of forms of market imperfections and thus are usually micro-founded in models of rent-sharing between employers and employees (Card et al., 2018). From this perspective, with this approach we identify the importance of rents in intergenerational transmission, instead of through aggregate shocks on market rents as in the cases of Arntz et al. (2025), Mocetti et al. (2022) and Raitano and Vona (2021), by directly pinpointing them at a much more granular level, that is, at the level of the individual firm.

A parallel emerging body of literature is exploiting the AKM framework to explore similar themes. Forsberg et al. (2024), Wilmers and Engzell (2024), and Zohar and Dobbin (2023) propose a decomposition of social mobility indices (IGE) using two-way fixed effect estimations. Their findings highlight a significant role for firm effects in explaining mobility, although these effects are generally less pronounced than the contribution of individual characteristics. At the same time, Forsberg et al. (2024), Wilmers and Engzell (2024) also suggest that a stricter view on the mediating role of education and, in particular, the specific case of graduates may provide further insights. Although contributing in a similar direction, our theoretical and empirical approach is more focused on studying transmission mechanisms than on decomposing social mobility. Rather than focusing on parent-son correlations, we align more closely with the two-stage approach employed by (Eliason et al., 2023) to study the impact of networks on firm-level wage premiums. Instead of focusing on parental influence in and along the life cycle, we follow this approach to identify the effect of parental background on the allocation across firms of workers under comparable job search conditions. This also helps to understand how background channels evolve over the labor market participation and also to strengthen the causal interpretation of the results. At the same time, restricting the sample to graduates from the same university helps isolate the portion of the background effect that is mediated by education, which account for a relevant share of individual fixed effects (Wilmers and Engzell, 2024) and shifts the focus on the matching process in the graduates' job market, whose peculiarities may also matter (Kramarz and Skans, 2014).

Estimating a residual background premium inherently requires considering individuals with equivalent education levels. Even when educational attainment is equalized, differences in the quality and specificity of educational qualifications related to family background persist. These proxies often lead to an overestimation of the residual wage premium because they fail to capture the nuanced advantages conferred by one's family. In this paper, we present a case study of graduates from the University of Modena and Reggio Emilia (UNIMORE henceforth), a medium-sized public university located in Emilia-Romagna, in the Northeast of Italy. Focusing on this specific institution and using detailed information about the degrees awarded, we can analyze wage disparities while effectively holding formal education constant. To conceptualize our approach, imagine a photograph taken during graduation day, featuring students tossing their caps in celebration. Although these students share a similar educational milestone, their backgrounds have influenced their journey to this point. Our analysis examines what happens next for these individuals in the labor market, aiming to understand how differences in their outcomes can be traced back to variations in their family backgrounds and disentangle between the transmission of unobservable abilities or differential opportunities for securing employment in higher-paying firms. To address this, we integrate insights from the literature on intergenerational transmission of advantages with the recent literature on the impact of firm-specific differences on wage inequality.

Our general findings indicate that parents' economic background significantly influences the allocation of workers to firms with different wage policies, consistently with the set of comparable evidence in Forsberg et al. (2024) and Wilmers and Engzell (2024). However, in the specific case under analysis, where these effects are strictly evaluated at equal levels and quality of education, the impact of parental background through firm effects is substantial and notably greater than that mediated by individual worker characteristics. This suggests that the influence of background on graduates operates primarily through firm sorting, rather than through observable individual characteristics. At the same time this evidence that the relevant role that background plays over worker individual abilities is mediated by education rather than by unobserved abilities.

We show that as workers transition from initial jobs to later positions, the advantage of better employment opportunities for those from higher socioeconomic backgrounds becomes more pronounced. Furthermore, when examining alternative outcomes, such as job duration and the likelihood of job-to-job transitions, we find strong connections with workers' backgrounds. This complicates causal interpretations when considering the entire trajectory in the labor market. To address such endogeneity concerns, we adopt a more focused approach by restricting our sample to first jobs and workers who find new employment following mass layoffs. This strategy follows the approaches of (Kramarz and Skans, 2014) and Eliason et al. (2023), respectively. Results show that when we consider workers in similar jo search conditions, i.e. for first jobs and unintended layoffs, the background impact on firm's premium increases. Compared to the overall picture, this suggest that the advantages provided by parental background are partially recovered during voluntary job changes. This occurs thus when the worker faces less urgency and has more time to find a new position, reinforcing the idea that a supportive background plays a key role in facilitating the search for companies with better wage policies. It also suggests that this advantage may stem from a reduced pressure to accept lower-paying jobs, or in general as effect of worse outside conditions.

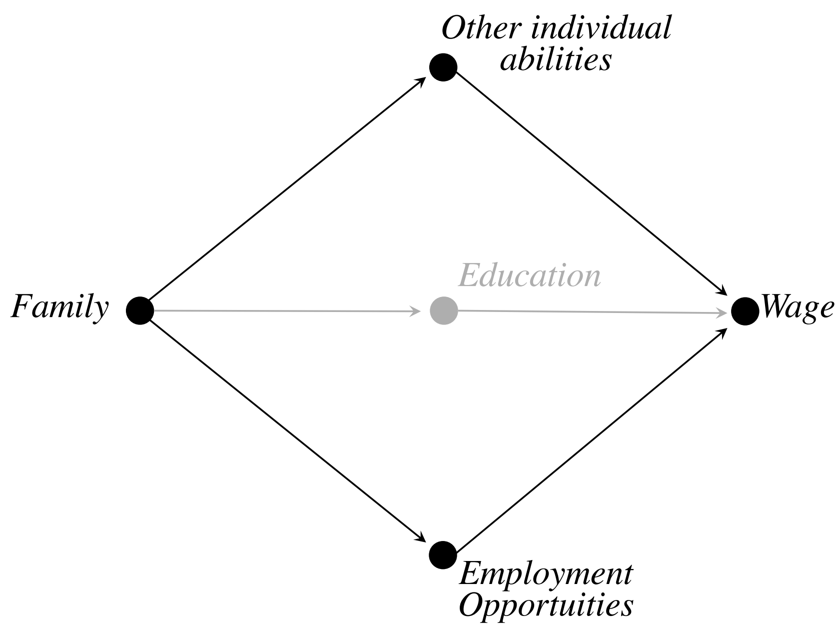
Following the path of the literature on AKM models, we interpret the covariance as an index of assortative matching between workers and firms between firm and worker fixed effects and assess whether the mechanisms underlying the better job opportunities available to graduates from more advantaged backgrounds contribute to improve matching quality. Our evidence suggests that the impact is, instead, negative.

The structure of this paper is as follows. Section 2 outlines the conceptual framework, which underpins both our econometric strategy and our data selection approach, discussed in further detail in Section 3. Section 4 details the methodology employed in our analysis, while Section 5 presents the results of the econometric analysis. Finally, Section 6 offers concluding remarks and suggests directions for future research.

2 Conceptual framework

The conceptual framework we adopt combines elements from two distinct bodies of literature: one that examines the effects of family background characteristics on workers' wages, and another that focuses on decomposing wages into firm and worker-fixed effects. We present a schematic overview of the first one in Figure 1 and then integrate the other framework in Figure 2.

Figure 1: The channels of influence of background on wages



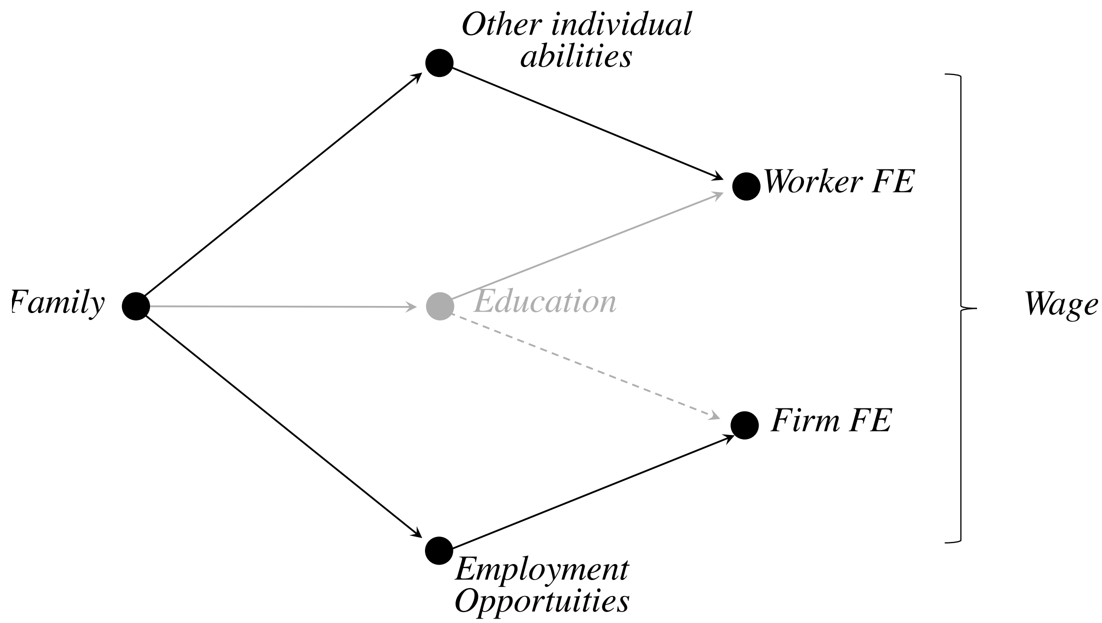
At the center, we have represented the main channel through which parental background impacts wages, that is education, specifically through the wage premium for education. We have shaded it brighter in gray the focus of the real analysis is precisely on the variety of mechanisms beyond this channel. However as previously mentioned, these mechanisms can be distinguished into two main categories.

- Channels affecting individual-specific characteristics: these are productive abilities or skills that are not directly related to formal education but are shaped by familial context and resources. Such skills might include personal attributes, informal training, or inherent talents nurtured by the family environment.

- Channels influencing employment opportunities: these channels operate by enhancing or limiting the ability of individuals to find employment in firms that offer superior wage policies. This encompasses socially integrated selection processes, where family background may provide access to networks, recommendations, or information as well as role models, segregation mechanisms, and anything that increases the likelihood of being employed by firms with better compensation structures.

Our goal is to develop a strategy that allows us to empirically disentangle these two effects. To this purpose, we integrate the second analytical framework, which allows us to identify two distinct components in wage determination: one at the individual level and the

Figure 2: The channels of influence of background on wages



other at the firm level. Accordingly, background effects can be assessed separately for each of the two components.

At this point, the AKM model's distinction is crucial for performing the necessary decomposition. By analyzing the relationships between family background and each of the two components of wages, worker and firm fixed effects, we can separately assess the impacts of family background on individual-specific characteristics and on the ability to secure employment in firms with advantageous wage policies. The general hypothesis is to identify the two distinct channels with the two-way fixed effects structure of the AKM model: the first channel relates to characteristics that would be equally rewarded across different firms, while the second channel pertains to the characteristics of the firm where the worker finds employment, regardless of the worker's attributes. This wage decomposition is represented in the right-hand side of Figure 2. In the middle, we represent the link we establish between the two frameworks, i.e., how the three channels on the left are connected with the two wage components on the right. Starting from education, which is generally regarded as a primary component of individual job characteristics, encompassing the skills and knowledge acquired through formal schooling. This connection is represented by the arrow in grey from education to worker fixed effects. Indeed, it is important to recognize that education, particularly certain qualifications, can also influence employment opportunities in contexts with better contracts or wage structures. This scenario is represented by the dashed arrow, indicating that education can affect both personal competencies and the likelihood of securing employment in favorable job contexts. Anyway, our focus is on the residual part of the parental effect, and we pursue it by considering graduates with the same quality and level of education, and thus this link lies in the background outside the analysis. Unlike the case of education, which we can consider acting on both wage components, the central step for this article is to consider, for the remaining links, only one link for each of the two channels with a different wage component, i.e. considering worker fixed effects as the wage premium for unobserved individual abilities and the firm fixed effects as the one for differential employment opportunities.

3 Data

3.1 Matched employer-employee data

Our main data source is the Italian National Social Security Institute (INPS), which maintains comprehensive employment records for all Italian workers and firms in the private non-agricultural sector. INPS gathers this information primarily through mandatory forms that employers submit periodically to fulfill their obligation of remitting social contributions on behalf of their employees. The details provided by the firms enable us to extract comprehensive information about the employment position and the individual holding that position.

The dataset includes variables such as annual gross earnings, the number of weeks worked per year, occupational categories (e.g., blue-collar, white-collar, middle managers, executives), gender, year of birth, and the first year of employment. While the dataset does not include hours worked, INPS provides a measure of full-time equivalent (FTE) weeks, which allows us to standardize and compare weekly wages between full-time and part-time employees.

Our analysis covers the period from 2005 to 2021. We limit our analysis to the largest connected set of workers and firms, a methodological restriction detailed in Section 4. In Table 1, we present descriptive statistics for the variables extracted from the INPS dataset. In the first column we report the full INPS data set and in the second one the subsample on which the AKM estimation is performed. The sample restriction results in a loss of nearly 1 percent of the total observations, primarily due to the exclusion of very small firms. The distribution of the variables used in the estimation is very close in the two models and provides an overall picture of the national labor market we are considering.

As previously explained, once the first-level estimations on the larger connected set are obtained, we integrate INPS data with additional information from the UNIMORE. This integration allows us to examine labor market outcomes by considering the economic background and specific characteristics of university graduates. To focus on recent entrants into the labor market, we consider individuals from the age of 23, the minimum graduation age, up to the age of 35. This age range ensures that the analysis is concentrated on the earlier stages of labor market participation, thereby limiting the data to information concerning the majority of graduates and not exclusively the older cohorts. To allow for a comparison, the third column of Table 1 reports the same variables from INPS, applying the same 23-35 age restriction. The differences observed when comparing this restricted sample to the whole sample are as expected: there is lower tenure, lower wages, a lower share of permanent contracts, and fewer individuals in managerial positions. Conversely, there is a higher share of apprentices.

3.2 UNIMORE data

We consider all graduates from the University of Modena and Reggio Emilia from 2005 to 2021. Using a k-anonymity restriction on one-to-one matching, we extract variables related to the type of degree, the final grade, and our main variable of interest, i.e., a proxy of the

Table 1: Descriptive statistics - Background variables

	2*All Sample	Largest Connected Set	All Sample 23-35	Matched Sample
Age	39.68	39.65	29.52	29.12
Tenure	18.76	18.75	9.11	7.93
FTE Weeks	36.41	36.46	33.39	35.12
Weekly wage	527.67	529.24	448.95	535.33
Full-time share	74.66	75.04	73.54	81.61
Permanent share	84.74	84.59	80.29	78.08
Blue collars share	55.52	55.61	53.76	10.75
White collars share	35.82	35.69	37.13	74.48
Executives share	0.64	0.65	0.06	0.18
Middle managers share	3.22	3.26	0.75	1.84
Apprentice share	4.80	4.80	8.31	12.75
Male share	58.91	59.13	53.76	41.80
Background				85.61
STEM				27.60
Master				55.02
Grade				53.34
Male				41.80
Workers	23,832,141	23,388,179	13,533,426	39,009
Firms	3,847,348	3,486,901	3,023,196	24,547
Observations	218,797,977	215,846,510	71,769,675	223,529

Notes: The first column shows averages on the INPS sample, the second column considers the subsample on which the AKM estimation is performed, the third column is on the subsample 23-35, and the fourth column includes only observations on workers in the UNIMORE-INPS dataset.

household economic background. This latter variable is a dummy taking value 0 if the student was exempted from paying university fees in the first year of enrollment. This exemption record provides a clear indicator of economic background as it is determined by a means test mechanism based on a measure of both income and family wealth, that is, the household "Equivalent Economic Situation Indicator" (ISEE) declaration, and the exemption threshold is periodically updated to account for inflation.

For the academic year 2023/2024, this threshold corresponded, in the absence of family wealth, to a total yearly income of 24,500 euros. By considering the whole sample of Unimore students, this threshold identifies approximately the first quintile of the distribution of Unimore students' parental economic conditions. As we will see below, the family background distribution at Unimore is the same as at the national level. It is thus a threshold which is effective, although not particularly low: the ISEE threshold level is approximately 2.5 times higher than the eligibility threshold for Italy's poverty assistance program, the *"Reddito di Cittadinanza"* (Baldini and Gori, 2019). Compared to analyses more focused on social mobility, which typically consider the average income of a parent or family when they are between 40 and 50 years old, our background indicator differs in two ways. First, it is a point-in-time measure, albeit situated roughly within the same age range as the parents, and it refers to conditions at the time of enrollment, which is more directly linked to the study's focus: graduates' path in the labour market. Second, it incorporates a more comprehensive economic indicator of family financial capabilities, as it integrates income together with wealth information. As to the variables that we will use as controls, the STEM variable is a dummy equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students and 0 to bachelor ones. Grade is a dummy variable indicating whether their GPA is higher than the average of their respective study programs in the same graduation cohort. Male is equal to one for male workers.

In the fourth column in Table 1, we show the same variables used in the first stage estimation, for the sample of the match between INPS-UNIMORE data sources. At the bottom of the fourth column, we also report the variables we select from UNIMORE archives. The comparison between the third and the fourth columns highlights the expected differences between a sample limited to young individuals with any educational level and a sample limited to young graduates.
In the estimation, we will also consider different observational levels (contracts and individuals) and other sample restrictions whose descriptive summary is reported in Table A.1 in the Appendix A.

Table 2: Descriptives of Italian Universities and Unimore

	Italian Universities	UNIMORE
Demographics		
Women	59.7%	56.5%
International students	3.2%	3.9%
Resident in same region	76.7%	76.1%
Degree Field		
Humanities and Education	17.8%	15.9%
Social Sciences and Law	37.1%	37.3%
Health and Agro-Veterinary	17.3%	17.7%
STEM	27.7%	29.1%
Household Social Class		
High	22.8%	23.0%
Medium white collar	32.2%	31.1%
Medium self employed	22.6%	24.4%
Executives	22.4%	21.5%
Parental Education		
None with degree	71.6%	73.0%
One with degree	17.5%	17.8%
Both with degree	10.9%	9.2%
Relevant Aspects in Job Search		
Acquisition of professionality	79.0%	78.0%
Career opportunities	64.0%	62.5%
Earning opportunities	59.2%	55.8%
Job stability	67.4%	64.8%

Notes: Data from Almlalurea 2005-2021

Finally, to strengthen the external validity of the results in our sample, we report some descriptive statistics of Unimore graduates in comparison with Italian graduates. To this purpose, we consider the public data source Almalaurea, which collects information about the vast majority of Italian universities and is responsible for the official Italian survey on graduates, used for evaluation purposes by the Italian Ministry of Education. The first two sections provide administrative data on the demographic characteristics of the graduates and their distribution by disciplinary area. Overall, there is a very good balance in our subsample. There is a slight underrepresentation of women, and the composition by geographic origin is very similar to that of the broader Italian population. Regarding the disciplines, the offerings at the University of Modena and Reggio Emilia cover all disciplinary areas, and within the various subgroups, the only ones not represented are those of the artistic and sports disciplines. Apart from this, the composition is once again similar between the two samples. To complete this comparison, we also present data from the survey, which has a response rate of around 90%, to check for any discrepancies in terms of family background and attitudes toward the labor market. We thus report the self-declared characteristics of each graduate's family in terms of educational background and the occupational social class of the parents, as well as their attitudes toward the labor market. For the latter, we consider the responses to questions concerning relevant aspects of the job search, reporting the percentage of students who consider each aspect to be highly relevant ('definitely yes'). As we can see in this case, the divergences between Unimore and the rest of the Italian universities are even less significant.

4 Methodology

Our methodology exploits a two-stage approach as in Bana et al. (2023) and Eliason et al. (2023), using firm and worker fixed effects estimated according to the methodology proposed by Abowd et al. (1999) in the second step. Eliason et al. (2023) use this estimation to analyze in a second stage the effects of peers' and parents' networks on the firm-specific wage component. In our case, rather than focusing on the impact of the direct and indirect links with employers, we focus directly on aspects of social mobility by analyzing the overall effect of family background. We estimate worker fixed effects and firm-specific wage premia of Italian workers and firms. We then investigate the relationship between these two distinct components of wages with workers' parental background.

We consider graduates from an Italian university, thus focusing on the segment of qualified workers. The use of a case study adds significant merit to the analysis from the perspective of the literature on intergenerational mobility. This approach allows us to investigate components beyond the commonly considered one, namely the relationship between background and education. By focusing on a specific group—individuals with the same levels of formal education (degree level, field, GPA, college)—we can obtain a robust measure of the *residual* background premium. The objective is not primarily to quantify this premium but rather to determine whether and how it can be decomposed into the two components of wages estimated in the first stage as explained in Section 2.

4.1 Two way-fixed-effects estimation

In this subsection, we present the first stage equation that follows the well-established methodology proposed by Abowd et al. (1999). Using yearly data from 2005-2021, we estimate firm premium from the equation:

$$w_{ijt} = \theta_i + \psi_{j(it)} + X_{it}\beta + \epsilon_{ijt} \tag{1}$$

The dependent variable represents log real weekly wages for individual i at firm j at time t; θ_i being individual fixed effects; $\psi_{j(it)}$ represents wage premium being paid by firm j with respect to a randomly chosen firm in the sample. X_{it} contains a cubic polynomial in age (normalized at 40), a set of dummies for occupations interacted with a cubic polynomial in experience (current year minus year of the first job as an employee), and a full set of time dummies. We exclude the linear term in age and in experience to avoid collinearity with time and ϵ_{ijt} represents an error term.

Worker level effects θ_i can be interpreted are worker wage premium that the workers would get in any firm he could be employed, i. e. the individual ability of the worker. One way to justify this component is to refer to the specific productive characteristics of the worker, and thus to human capital in its general dimensions. Firm-level effects ψ_j instead are wage components representative of firms' wage-setting policies practiced by firms to all employees (Card et al., 2013). Firm premia may be flexibly interpreted as something that derives from market power, efficiency wage, or strategic wage posting behavior (Mortensen, 1998; Cahuc et al., 2014) or time-invariant factors which may reflect the surplus produced by the firm (Card et al., 2016) and they can be related to compensating differentials literature (Sorkin, 2018; Bana et al., 2023). In such a framework, since productivity is not the sole determinant of wages, also the background effect might be channeled into them by these further determinants (Franzini et al., 2020). Indeed, parental background is an individual-specific characteristic that may cast an influence on θ_i through the transmission of productive abilities but it could also lead the worker towards a specific firm j at time t. In other words, the worker may earn a certain firm premium because parents may drive their children towards a certain company that applies a certain pay policy to their workers, the direction of this influence is to be investigated (Kramarz and Skans, 2014).

To estimate equation (1), we use a panel at the worker level that spans from 2005 to 2021. Additionally, considering that workers may hold more than one job in a year, we prioritize the main job based on contract type and wage. Specifically, if a worker has two jobs in a year and only one is permanent, we select the permanent position. If both jobs are of the same type, we select the higher-paying one. By restricting our analysis to this set, we concentrate on 99% of the observations in our panel.

Given the importance of worker mobility in identifying firm fixed effects, we focus on the largest firms-workers connected set, and we proceed with the estimation of equation (1) following the approach outlined by Abowd et al. (2002). Finally, we end up with so-called firm premia which are our main variable of interest. To have unbiased estimates, the main assumption behind AKM models is so-called exogenous mobility. To be more specific, workers may move between firms following some pattern, as is the case in our hypothesis that some workers fixed characteristics might impact firm sorting, but what is important is that mobility is not related to components of the error term in equation (1). For, if there was an idiosyncratic "match effect" to drive mobility, and a worker-specific surplus may occur from the match with a certain firm, we would be mistakingly attributing this effect to firm-specific wage premia common to all workers employed at that firm. Another potential concern related to the estimation of firm premia is that employees might be inclined to depart from companies undergoing downturns and join those undergoing upturns. If this holds, we could observe a dip in the wages of departing employees shortly before their departure, alongside notable wage growth among recent hires Ashenfelter (1978). To test this assumption, Card et al. (2013, 2016) have developed an empirical routine that we will follow to test our identification hypothesis. The test for exogenous mobility will be presented in Subsection 4.3. This hypothesis does not exclude assortative matching between firms and workers, whose measurement is a core issue in the AKM literature. An unbiased estimation of these sorting effects would involve a deeper insight by correcting with leave-out estimators or similar finer analysis (Kline et al., 2020). In our analysis, we are mainly interested in the direction of the effect of the background rather than in the magnitude, thus we will not delve deeper. Hence in the second stage, as a measure of assortative matching, we will use its textbook version, i.e., the correlation between firm and worker fixed effects obtained estimating equation (1) (Abowd et al., 2002; Andrews et al., 2008).

4.2 Analysis of the background wage premium

Together with log wages, the decomposition of wages obtained in the first level estimation is used in the second stage in six OLS models with six different dependent variables to analyze the impact of workers' parental background.

The estimated equations are all specified as follows:

$$y_{ijt} = \gamma z_{ijt} + \delta C_i + \zeta_{ijt} \tag{2}$$

where y_{ijt} are log real weekly wages or alternatively, the wage components estimated in the first stage for person i working in the firm j in the year t; C_i includes control variables such as gender, year and cohort fixed effects and information on the degree (grade, field, level); ζ_{ijt} is the error term. z_{ijt} represents the background dichotomous variable. The coefficient γ is thus the one of interest. By considering the notation for equation (1) the coefficient relative to the model where $y_{ijt} = w_{ijt}$ will be the overall background premium (beyond education), that we observe in our sample. The coefficient on the model with worker fixed effects θ_i as the dependent variable will show the component of the background channels that impact individual fixed effects, that is, wage premium that are related to individual productive abilities. The coefficient of the model on the firm-level effect ψ_j provides us with the relationship between the family background of a graduate and the premium she earns because of being employed in a firm that has a higher firm wage premium. The hypotheses underlying the AKM methodology allow us to interpret firm fixed effect as firm-specific wage premium that firms would pay independently from their specific employers. The background channel we are thus considering, in this case, is indirect, that is, background features may impact the opportunity of a graduate to be sorted into a better-paying firm.

The fourth dependent variable considered is the correlation between workers' and firms' fixed effects. Accordingly to the discussion presented in Subsection 4.1, in this case the coefficient γ will tell us whether the background channels favor or hinder the assortative matching between firms and workers.

To consider the extent to which the two-way fixed-effects model explains the overall background premium, we will also estimate the same equation (2) for the two other components of the equation (1). One is the component of wages that is related to the covariates of the equation (1), i.e. the predicted values $X_{it}\beta$, that include time-varying components and matches specific information such as tenure, occupation, and their interactions. The other is the residual of the estimation ϵ_{ijt}.

In some estimations, the sample of the analysis includes multiple observations for the same individual, either across different firms or within the same firm. Since we are interested in a characteristic, background, which is at the student level, we weigh observations by the inverse of the number of observations concerning the same individual. This approach is not far from taking the individual's average of the independent variable within the sample. Results obtained without weights or directly using individual averages are strongly robust.

The first sample we will consider concerns all firm-worker pairs among our observations, i.e. all different contracts, by taking the wage in the first year if the contract lasts more than one year. However, career paths in the labor market can vary significantly, and this is particularly true for the entry of young people. Thus we will consider different subsamples of the previous one. We first split and examine separately the first jobs and eventual subsequent jobs. Then, we narrow our focus to workers who have moved from a previous firm due to a mass layoff. This restriction allows us to analyze the impact of involuntary job changes on career paths and wage outcomes. We define a mass layoff as a situation where a firm reduces its workforce by more than 30%. Both the first and the last restrictions allow to foster the causal interpretation of the results since they consider workers who are seeking new employment under similar conditions. The strategy of focusing on first jobs follows the work by (Kramarz and Skans, 2014), while the restriction to mass layoff is commonly used in the literature (see Eliason et al. 2023).

Finally, we consider the characteristics of the matches in terms of contract features, estimating the same model as in equation (2) using as dependent variables the probability of having a permanent contract or a full-time job. Next, we shift our focus back to all job changes by analyzing the probability of staying with the same firm in the following year. For those who do change firms, we also examine the likelihood of moving to a firm with a better fixed effect than the previous one, as to verify possible cumulative effects.

4.3 Two-way fixed effect results

The ability to separate the two components of fixed effects — individual effects and firm effects — is contingent upon the assumptions of exogenous mobility discussed in the methodology. To test the exogenous mobility assumption in our first stage analysis, we follow the routine in Card et al. (2013, 2016). First of all, we calculate the mean wages of coworkers for individuals who change jobs in a certain year. Then, we define the average wages of movers up to two years before and after a move and we rank these averages based on the quartile of origin and destination of one's coworker wages. Thus, we end up with 16 cells formed as a combination of each quartile of mean coworkers' wages in the old and new firms. For clarity, we report on Figure 3 mean wages from those who start from the first or the last quartile of the distribution of coworker wages.

Looking at Figure 3, it is reasonable to state that the exogenous mobility assumption may be accepted. If there were match effects like the ones defined, for instance, by dynamic match models (Eeckhout and Kircher, 2011), the difference in firm premia before and after a move (here proxied by coworker wages) would not represent firm wage premia only. If this was the case the estimates would be biased and the additive specification strongly disputable. However, looking at the symmetry of wage trajectories before and after a move, it seems that there is no general premium on moving. Furthermore, we do not see sudden drops in wages before the move and a rise afterward: this should mean that we do not have unobservable negative shocks on firms which could lead workers to move to better firms, if this were the case an "Ashenfelter dip" would appear. The same line of reasoning could apply to shocks in individuals' productivity which could be correlated with mobility and wages. Of course, this test does not prevent mobility from having systematic patterns. Skilled workers may be

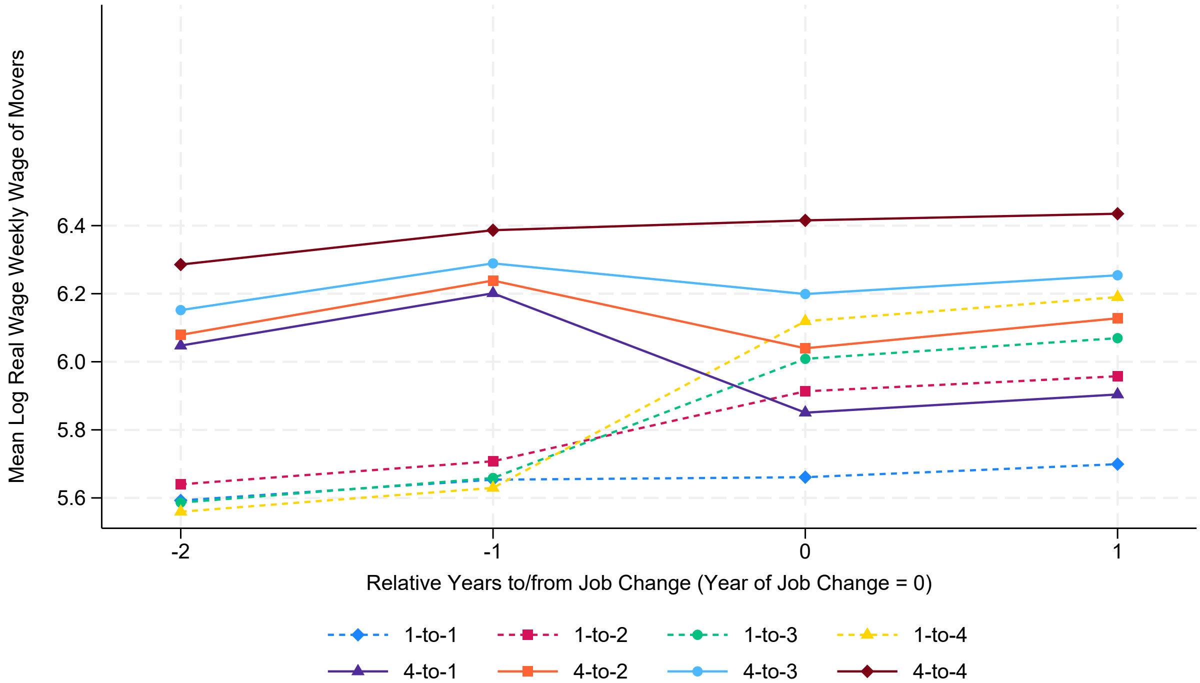


Figure 3: Mean weekly earnings of movers across quartiles of average coworker weekly earnings. Data relate to 2005-2021 period.

more likely to engage in on-the-job search and to be employed in high-wage firms as in Hall and Krueger (2012) and Card et al. (2018). Furthermore, skilled workers may a have better parental background that may help them find a job in a high-wage firm. This does not bias our estimates because we control for this via time-invariant workers' characteristics.

Once we have checked for our identification hypothesis we estimate equation (1) on the larger connected set. The main output of the estimations is reported in Table 3. The correlation between workers' and firms' effects is positive, i.e. assortative matching is observed, and in general, the main features of the application of the AKM model in previous studies on Italy are confirmed (Casarico and Lattanzio, 2024; Macis and Schivardi, 2016).

5 Results

After estimating fixed effects for Italian workers and firms, we match these data with our sample of graduates to focus on the background wage premia and its components. As previously mentioned, we will begin by considering all contracts and then examine subsamples corresponding to different phases of the labor market path. The restrictions to first jobs and jobs following mass lay-off allow tackle with endogeneity issues as discussed in subsection 4.2. Finally, we will consider some alternative labor market outcomes.

5.1 The residual background premium

We start by examining the estimation of the equation (2) on all the worker-firm matches in the sample, i.e. all the different contracts. Results are shown in Table 4. The first column of the

Table 3: Summary of AKM estimation, principal job - Italian Private Sector 2005-2021

	All sample	Largest Connected set
Sample size		
Workers	23,832,141	23,388,179
Firms	3,847,348	3,486,907
Summary Statistics		
Observations	218,797,977	215,846,510
Mean log wages	6,116	6,119
Standard deviation of log wage	0,447	0,448
Summary of estimates		
Standard deviation of firm effect		0,207
Standard deviation of worker effect		0,294
Correlation of worker/firm effects		0,147
RMSE of AKM residuals		0,22
Adjusted R2		0,725

table presents the coefficient of the economic background variable on the estimation of (log) wages. This reveals a substantial residual premium associated with economic background: among individuals with the same formal education, there is a background wage premium of 5.4%. It is worth recalling that this variable differentiates between individuals who fall above or below a threshold corresponding approximately to the bottom quintile of family economic conditions. Control variables exhibit the expected signs, showing a wage premium for STEM fields, higher levels of education, higher GPA's and males.

Table 4: Results - All contracts

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.0535***	0.0187***	0.0347***	-0.0509***	-0.0035	0.00365
	(0.00616)	(0.00267)	(0.00276)	(0.0176)	(0.00225)	(0.00405)
STEM	0.0665***	0.0608***	0.0199***	0.0671***	-0.0013	-0.0128***
	(0.00515)	(0.00263)	(0.00225)	(0.0160)	(0.00229)	(0.00379)
Master	0.00388	0.00858***	-0.0283***	-0.0870***	0.00494**	0.0186***
	(0.00437)	(0.00210)	(0.00203)	(0.0130)	(0.00193)	(0.00323)
Grade	0.0921***	0.0388***	0.0340***	-0.141	0.00244	0.0168***
	(0.00429)	(0.00212)	(0.00195)	(0.0130)	(0.00192)	(0.00320)
Male	0.0990***	0.0799***	0.0563***	0.0889***	-0.00338*	-0.0339***
	(0.00464)	(0.00229)	(0.00211)	(0.0140)	(0.00205)	(0.00343)
Constant	6.280***	0.0429	3.058***	0.444***	-0.00743	3.115***
	(0.0508)	(0.0377)	(0.0181)	(0.144)	(0.0322)	(0.0535)
Year FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Observations	75413	75413	75413	75413	75413	75413
R-squared	0.14	0.238	0.092	0.024	0.001	0.083

Notes: Robust standard errors in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

The next two columns report the results of the estimations that consider as dependent variables the wage components estimated in the two-way fixed effects first stage, and which are the main focus of our analysis. Both of these wage components show significant and positive coefficients for the background variable. Notably, the firm-level channel exhibits a higher coefficient, suggesting that economic background has a pronounced impact on workers' wages through the firm-level channel. The coefficient for the background variable in the individual ability model is also significant, though relatively lower. This indicates that while family background still significantly shapes individual abilities beyond the educational channel, its impact is conveyed to a relatively greater extent through the opportunities provided by employment in firms with different wage policies.

The fourth column shows the coefficients related to the correlation between the two effects. In both the overall Italian national sample and the matched sample from UNIMORE, the correlation between the two effects is positive, indicating an assortative matching between firms and worker types, consistent with the AKM literature. When considering this correlation as the dependent variable, the background variable shows a negative coefficient. According to the discussion in subsection 4.2 we can state that the background channel negatively affects assortative matching.

The final two columns display the correlation with the residual components from the first-stage estimation, namely the residuals and covariates. The lack of significance and nearly null coefficients of the residuals confirm the effectiveness of the decomposition performed. The lack of correlation also concerns first-stage covariates.

To delve deeper into the overall findings, we explore stratifications of the sample with the variables drawn from both data sources, as reported in Figure 4. In this Figure, we plot the coefficients and the confidence intervals of the log wages and the two fixed effects components for the model in 4, stratified by two individual-level and two firm-level general characteristics. For the individual-level variables, we report gender and GPA. These variables allow us to assess how personal attributes influence wage outcomes and the associated fixed effects components. As to the firm-level characteristics, we consider broad sectors and the firm's employment dimension.

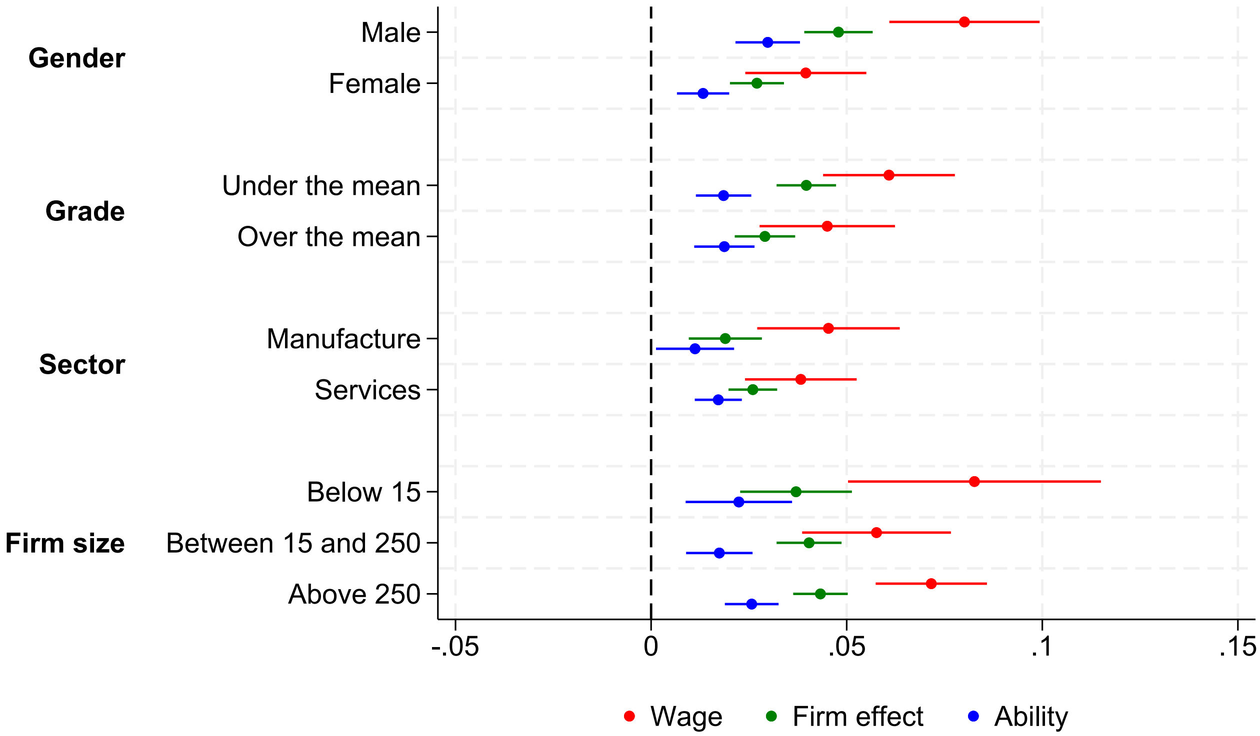
The gender dimension shows a significant difference in the overall level of coefficients. This finding aligns with the existing literature that analyzes gender differences in the context of firm fixed effects (Casarico and Lattanzio, 2024; Card et al., 2016). However, the relative distinction between the two channels persists, as the individual ability channel also contributes to a lower extent than the employment opportunity channel. The other dimension considered at the individual level, as shown in Figure 4, is the graduation grade, expressed as above or below the average for the same year in the same course. For students with lower grades, the firm channel holds relatively greater importance, indicating that the types of firms employing these students significantly impact their wage outcomes. Conversely, students with higher grades experience more substantial background effects through the individual ability channel.

As expected, the stratifications by firm characteristics are less heterogeneous compared to individual characteristics, confirming the robustness of the results. In the services sector, the overall background premium is lower, but this difference is not statistically significant. Larger firms seem to have a more pronounced ability channel, but again, the difference is not significantly appreciable.

These findings indicate that, although there are variations in the overall wage premium between sectors and firm sizes, these differences are not substantial enough to significantly alter the general conclusions.

The literature employing the AKM decomposition to break down intergenerational mobility indices, as previously discussed, has highlighted a significant, albeit not predominant,

Figure 4: Results - Stratifications of economic background



Notes: The legend lists the dependent variables we consider. The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. The horizontal lines represent 95 percent confidence intervals based on robust standard errors. We control for STEM, Master, Grade, Male, year and cohort fixed effects in all the regressions. Robust standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

role of firm-fixed effects. This contrasts with our findings, where firm-fixed effects appear more prominent. First, it is important to consider the different national contexts examined (Forsberg et al., 2024) and Wilmers and Engzell (2024); for instance, consider the case of Sweden, while Zohar and Dobbin (2023) focus on Israel. In all cases, firm-fixed effects account for a minimal share of overall wage inequality—less than 20% of the variance explained by worker effects. In our study, however, the firm component plays a much more substantial role, aligning with previous estimations for Italy and, more broadly, with the literature on core European countries (Card et al., 2013, 2016) and the US (Bana et al., 2023; Sorkin, 2018). Secondly, the restriction to graduates from the same university and the use of additional controls on formal education in the second stage specifically excludes the portion of the relationship with background mediated by education. In other words, the reduced role of individual effects indicates that a substantial part of the relationship between background and individual fixed effects operates through education—a hypothesis suggested by Wilmers and Engzell (2024). Lastly, rather than focusing on the relationship between background and the average firm-fixed effects over time that a worker benefits from, our focus is directly on individual hiring episodes to identify the direct impact of background on worker-firm matching, which we will explore in detail in the next section.

5.2 The path in the labor market

In the main analysis, we have considered all contracts in the matched sample and thus pooled together different phases of the graduates' careers. To delve deeper into the labor market paths we consider alternative sample restrictions. As explained in Section 4, these restrictions identifying the background effect under more specific and comparable circumstances, also allow us to strengthen the causal interpretation of the results.

Table 5 summarizes the results by reporting only the coefficient of interest. Full results are shown in the Appendix B. To ease the comparison, the first row just reports the same coefficients of interest shown in the first row of Table 4. In the second row, we report the estimation on the subsample of observations concerning only the first job observed for each individual. The background premium is slightly lower. The coefficient on worker fixed effects is substantially the same; indeed, in both cases the coefficient refers to a variable that is fixed at the individual level, and the individuals in the two samples are the same. The slight difference in the estimated coefficients can be attributed to the role of the time dummy variables, which are not individual-level variables, and therefore the data differ. The coefficient of the other component, firm fixed effects, moves in the same direction as that on wages. The lower background premium can thus be related to the reduced strength of the firm channel in the context of first jobs. The impact of family background may manifest more strongly later in their careers when career progression opportunities become more pronounced. The coefficient on the fixed effects covariance is essentially the same as the benchmark case.

Table 5: Results - The path in the labor market

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
All contracts						
Coeff	0.0535***	0.0187***	0.0347***	-0.0509***	-0.0035	0.00365
SE	(0.00616)	(0.00267)	(0.00276)	(0.0176)	(0.00225)	(0.00405)
Obs.	75413	75413	75413	75413	75413	75413
First jobs						
Coeff	0.0407***	0.0182***	0.0326***	-0.101***	-0.00362	0.00654
SE	(0.00844)	(0.00309)	(0.00375)	(0.0270)	(0.00296)	(0.00567)
Obs.	39009	39009	39009	39009	39009	39009
Further jobs						
Coeff	0.0688***	0.0231***	0.0350***	-0.0423*	-0.000637	0.0114*
SE	(0.00797)	(0.00344)	(0.00375)	(0.0253)	(0.00398)	(0.00630)
Obs.	31025	31025	31025	31025	31025	31025
Mass layoffs						
Coeff	0.106***	0.0265***	0.0539***	-0.107	-0.0133	0.0392**
SE	(0.0239)	(0.00797)	(0.0105)	(0.0754)	(0.00944)	(0.0170)
Obs.	5621	5621	5621	5621	5621	5621

Notes: Robust standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Full results in Appendix B.

The third row reports the estimation of all job transitions, i.e., relative to year-to-year job changes. As expected, the difference with the benchmark estimation is exactly in the opposite direction compared to the first jobs. In this case, the estimated coefficient of the component of the AKM decomposition captured by the covariates becomes significant, suggesting a possible explanation based on the match-specific covariates of the first stage estimation. The evidence in the subsequent analysis in Table 6 will confirm such a hypothesis.

In the last row of Table 5 we report the estimation on the subsample of contracts following a separation due to mass layoff as explained in Section 4. All the effects strongly reinforce, with the background premium increasing to 10%. This indicates that under conditions of involuntary job changes, the influence of family background becomes even more pronounced, suggesting that parental effects are stronger in more adverse conditions.

Again, the coefficients of the models of the two fixed effects components move less than the coefficient on overall wages, though in the same direction. The firm component increases to 5.4%. This highlights the reinforcement of the background premium through the labor market path, consistent with the progressive increase in the overall background premium. The component of the covariates from the first stage is significant, as observed in the previous case.

Given the importance of firm characteristics, it is also plausible to consider that wage policies are connected to the job's qualitative aspects. Therefore, we delve into these aspects by considering the relation of the background with the contractual features of the jobs.

Table 6: Results - Alternative outcomes

	Full time	Permanent	Change firm	Better firm
Background	0.0554***	0.0622***	-0.0398***	0.0251***
	(0.00482)	(0.00544)	(0.00346)	(0.00866)
STEM	0.0725***	0.0665***	-0.00644**	0.0414***
	(0.00364)	(0.00468)	(0.00262)	(0.00776)
Master	-0.0491***	-0.00444	-0.00498***	-0.0265***
	(0.00358)	(0.00421)	(0.00231)	(0.00670)
Grade	0.0356***	0.0438***	-0.0282***	0.00489
	(0.00347)	(0.00408)	(0.00226)	(0.00655)
Male	0.133***	0.0813***	-0.0022	0.0403***
	(0.00355)	(0.00436)	(0.00240)	(0.00707)
Constant	0.740***	0.746***	0.180***	0.443***
	(0.0328)	(0.0330)	(0.0284)	(0.120)
Year FE	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES
Observations	75413	75413	177611	31025
R-squared	0.072	0.064	0.018	0.013

Notes: The analysis on Full-time and Permanent considers all contracts. "Better firm" considers the subsample of workers who have changed firms from year to year. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In the first two columns of Table 6, we report the estimations of the same as equation (2) by taking permanent and full-time employment as dependent variables. Family characteristics prove to be significant determinants in both obtaining a permanent contract and securing a full-time schedule.

Complementing this evidence, the third column shows the model estimate on the probability of remaining with the same firm the following year. The evidence supports the findings on permanent employment, showing a positive background effect on tenure within the firm.

The increase in background premium in successive jobs suggests that there may be mechanisms that persist over time and amplify the effects of background. To investigate this, in the fourth column of Table 6 we examine the probability of individuals moving to a firm with higher fixed effects than their previous one, as an alternative dependent variable for those who change firms from one year to the next. The sign and value of the coefficient evidence a cumulative effect and confirm that the selection mechanism among firms strengthens career paths within the labor market.

6 Conclusions

This paper has contributed to the analysis of the relationship between intergenerational inequality and differences in pay policies between firms, shedding light on the persistence of income inequality across generations. Since we were interested in channels other than education, we have focused on graduates and considered the case of the University of Modena and Reggio Emilia. In line with the literature (Lam and Schoeni, 1993), the general evidence shows that family background plays a significant role in determining wage premia well beyond the differential opportunities offered in attaining the educational level. Indeed, although the data and the case study allow us to reasonably fully control for the education attained, the wage differences related to family backgrounds are still large: belonging or not to the bottom 20% of the distribution of family earning capacity corresponds to a wage premium of 4% on first jobs and overcomes 5% on all contracts. In this framework, by exploiting the AKM methodology we have estimated firm and worker fixed effects to verify whether beyond the transmission of individual abilities not proxied by education, a background premium also comes from the opportunities to be employed in firms having better wage policies. We show that this further channel is not only significant but also prevalent compared to the transmission of unobserved abilities. This indicates that the advantage conferred by a better family background is primarily due to the ability to secure employment in firms with superior wage policies rather than inherent individual abilities that are not captured by education. This main result is robust across different estimations and stratifications. Compared to the recent literature that is emerging and attempting to decompose overall social mobility indices using the AKM methodology (Forsberg et al., 2024; Wilmers and Engzell, 2024; Zohar and Dobbin, 2023), our findings indicate that firm fixed effects are more relevant than individual effects. While this literature has primarily focused on cases such as Sweden—where firm effects generally play a smaller role—this contrasts with the United States and most European countries, including Italy, which is the focus of this study. However, this significant difference can be attributed to the distinct perspective of our study, as we focus on transmission mechanisms beyond education, particularly among university graduates.

From this standpoint, we can conclude that a substantial part of the intergenerational transmission of workers' individual capabilities occurs through investment in and performance in education. Once this primary channel is properly accounted for, the residual transmission of abilities remains significant but loses its central role while firm sorting effect becomes primary. This result is also consistent with recent studies that have significantly downplayed the role of genetics in intergenerational transmission (Bingley, Cappellari 2024).

At the same time, our distinct focus and methodological approach have allowed us to highlight how firm fixed effects become even more critical when considering individuals under the same job search conditions, such as those experiencing involuntary layoffs. This also suggests that individuals from disadvantaged backgrounds can partially overcome their initial disadvantage through voluntary job transitions. Moreover, this is also consistent with further evidence showing that background effects on firm sorting become more pronounced as individuals progress in the labor market, positively influencing the probability that job changes will lead to employment in firms with better fixed effects and improved contractual arrangements.

There are many possible interpretations of the firm selection channel of background transmission. Some interpretations could include the tacit transmission of aspirations or a better understanding of how the labor market operates. For instance, individuals from more advantaged backgrounds may be more aware of better job opportunities due to their social networks and family guidance. This knowledge can lead them to apply for and secure positions in higher-paying firms. Workers from well-connected families might receive job referrals from their network, giving them an edge in securing desirable positions.

Additionally, there are non-informational explanations to consider. Different outside options also play a role; those with better financial support can afford to be more selective in their job search, avoiding lower-quality positions and holding out for better opportunities. This can be particularly advantageous during periods of unemployment or job transitions, coherently with our analysis of the transition from mass layoffs. Moreover, the psychological aspect of confidence and self-efficacy influenced by family background cannot be ignored. Individuals from supportive and resourceful families may approach job searches with greater confidence, persistence, and resilience, which are crucial traits for navigating the labor market successfully. When considering the correlation between the two fixed effects, the background variable shows a negative effect. This means that for graduates coming from better economic backgrounds, the firm-worker type matching is worse. If assortative matching between firms and workers corresponds is efficient, this finding suggests that the channels related to family background have a controversial effect as long as the advantages conferred by a better economic background may not always lead to optimal employment matches, potentially due to overconfidence, mismatches in job expectations, or reliance on non-meritocratic advantages.

In a labor market rewarding features other than human capital, such a system produces perverse incentives that can push people from disadvantaged backgrounds to rationally self-segregate if they cannot bridge the gap in receiving the same rewards despite investing in education. This scenario results in lower social mobility, poor talent allocation, and reduced human capital accumulation. Indeed, when individuals from less privileged backgrounds realize that the labor market disproportionately favors those with better social connections, referrals, and other non-meritocratic advantages, they may become discouraged. This discouragement can lead them to avoid competitive fields or high-investment career paths, perceiving that their efforts will not yield comparable rewards. Consequently, the potential of talented individuals from disadvantaged backgrounds is underutilized, leading to a suboptimal allocation of talent across the economy. Furthermore, the lower accumulation of human capital among these individuals can have long-term negative effects on economic growth and innovation.

The evidence on the residual background premium, particularly its component that cannot be attributed to the worker's productive features, suggests some theoretical reflections and opens new perspectives for further developments. First of all, it urges us to consider the origin of these wage premia and the issues of equality of opportunity in a context where non-competitive market characteristics, particularly in the labor market, make the process of worker allocation to firms crucially dependent on family background. In other words, it means looking at aspects of intergenerational transmission that concern the ability to position oneself in a rent-seeking context. This perspective inverts the trade-off between efficiency and equality, indicating that higher rent-seeking opportunities are accompanied by greater inequality, especially in its intergenerational dimension. This is because the economic conditions of the family impact an individual's ability to extract these rents.

Finally, in the pursuit of equal opportunity objectives, all this highlights the need to resort to a mix of policies beyond just those related to education. This can include various instruments across different dimensions of policy intervention. Regulatory interventions, such as the liberalization of professions, can reduce barriers to entry and create more equitable opportunities for all. Additionally, more efficient supply-demand matching systems can help align job seekers with suitable employment opportunities, regardless of their background. Job mentoring policies can guide also individuals through the complexities of the labor market, helping them make informed career choices and improving their chances of securing quality employment.

Finally, social security policies might also play a crucial role. More extensive unemployment protection systems can provide a safety net for individuals during job transitions, reducing the economic pressure that may otherwise lead them to accept suboptimal job offers.

References

Abowd, J.M., Creecy, R.H., Kramarz, F. (2002). Computing person and firm effects using linked longitudinal employer-employee data. *Longitudinal Employer-Household Dynamics Technical Paper no. 2002-06, Center for Economic Studies, US Census Bureau, Washington, DC.*

Abowd, J. M., Kramarz, F., Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2), 251-333. Wiley Online Library.

Agnarsson, S., Carlin, P.S. (2002). Family background and the estimated return to schooling: Swedish evidence. *Journal of Human Resources*, 37, 680-692.

Andrews, M. J., Gill, L., Schank, T., Upward, R. (2008). High wage workers and low wage firms: Negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 171(3), 673-697.

Arntz, M., Lipowski, C., Neidhofer, G., Zierahn-Weilage, U. (2025). Computers as Stepping Stones? Technological Change and Equality of Labor Market Opportunities. *Journal of Labor Economics.*

Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *The Review of Economics and Statistics*, 60, 47-57. JSTOR.

Autor, D.H., Katz, L.F., Kearney, M.S. (2008). Trends in US wage inequality: Revising the revisionists. *The Review of Economics and Statistics*, 90, 300-323.

Baldini, M., Gori, C. (2019). Il reddito di cittadinanza. *il Mulino*, 68(2), 269–277.

Bana, S., Bedard, K., Rossin-Slater, M., Stearns, J. (2023). Unequal use of social insurance benefits: The role of employers. *Journal of Econometrics*, 233(2), 633-660. Elsevier.

Barth, E., Bryson, A., Davis, J.C., Freeman, R. (2016). It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States. *Journal of Labor Economics*, 34(S2), S67-S97. University of Chicago Press Chicago, IL.

Bavaro, M., Patriarca, F. (2022). Referrals, intergenerational mobility and human capital accumulation. *Economic Modelling*, 110, 105811.

Bowles, S., Gintis, H., Osborne Groves, M. (2009). *Unequal chances: Family background and economic success.* Princeton University Press.

Cahuc, P., Carcillo, S., Zylberberg, A. (2014). *Labor economics.* MIT press.

Card, D., Cardoso, A.R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1), S13-S70. University of Chicago Press.

Card, D., Cardoso, A., Kline, P. (2016). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly Journal of Economics*, 131(2), 633-686

Card, D., Heining, J., Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics*, 128(3), 967-1015. MIT Press.

Casarico, A., Lattanzio, S. (2024). What firms do: Gender inequality in linked employer-employee data. *Journal of Labor Economics*, 42(2), 325-355. The University of Chicago Press Chicago, IL.

Corak, M., Piraino, P. (2011). The intergenerational transmission of employers. *Journal of Labor Economics*, 29, 37-68.

Eeckhout, J., Kircher, P. (2011). Identifying sorting—in theory. *The Review of Economic Studies*, 78(3), 872-906. Oxford University Press.

Eliason, M., Hensvik, L., Kramarz, F., Skans, O.N. (2023). Social connections and the sorting of workers to firms. *Journal of Econometrics*, 233(2), 468-506. Elsevier.

Forsberg, E., Nybom, M., Sthuler, J. (2024). Labor-market drivers of intergenerational earnings persistence. *Mimeo*.

Franzini, M., Patriarca, F., Raitano, M. (2020). Market competition and parental background wage premium: the role of human and relational capital. *The Journal of Economic Inequality*, 18, 291-317.

Granovetter, M.S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6), 1360-1380. University of Chicago Press.

Granovetter, M. (1983). The strength of weak ties: A network theory revisited. *Sociological Theory*, 1, 201-233. JSTOR.

Hall, R.E., Krueger, A.B. (2012). Evidence on the incidence of wage posting, wage bargaining, and on-the-job search. *American Economic Journal: Macroeconomics*, 4(4), 56-67. American Economic Association.

Hudson, J., Sessions, J.G. (2011). Parental education, labor market experience and earnings: New wine in an old bottle?. *Economics Letters*, 113, 112-115.

Kline, P., Saggio, R., Sølvsten, M. (2020). Leave-out estimation of variance components. *Econometrica*, 88(5), 1859-1898. Wiley Online Library.

Kramarz, F., Skans, O.N. (2014). When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies*, 81(3), 1164-1200. Oxford University Press.

Lam, D., Schoeni, R.F. (1993). Effects of family background on earnings and returns to schooling: evidence from Brazil. *Journal of Political Economy*, 4, 710-740.

Macis, M., Schivardi, F. (2016). Exports and wages: Rent sharing, Workforce composition, or Returns to skills? *Journal of Labor Economics*, 34(4), 945-978. University of Chicago Press.

Magruder, J.R. (2010). Intergenerational networks, unemployment, and persistent inequality in South Africa. *American Economic Journal: Applied Economics*, 2, 62-85.

Mocetti, S. (2016). Dynasties in professions and the role of rents and regulation: Evidence from Italian pharmacies. *Journal of Public Economics*, 133, 1–10.

Mocetti, S., Roma, G., Rubolino, E. (2022). Knocking on parents' doors: Regulation and intergenerational mobility. *Journal of Human Resources*, 57(2), 525–554.

Mortensen, D.T. (1998). Equilibrium unemployment with wage posting: Burdett-Mortensen meet Pissarides. *University of Aarhus CLS Working Paper*, 98-014.

Raitano, M., Vona, F. (2018). From the cradle to the grave: The influence of family background on the career path of Italian Men. *Oxford Bulletin of Economics and Statistics*, 80, 1062-1088.

Raitano, M., Vona, F. (2021). Nepotism vs. specific skills: The effect of professional liberalization on returns to parental background of Italian lawyers. *Journal of Economic Behavior & Organization*, 184, 489–505.

Sorkin, I. (2018). Ranking firms using revealed preference. *The Quarterly Journal of Economics*, 133(3), 1331-1393. Oxford University Press.

Wilmers, N., Engzell, P. (2024). Firms and the intergenerational transmission of labor market advantage. *The University of Chicago Stone Center Working Paper Series*, (24-04).

Zohar, T., Dobbin, C. (2023). Quantifying the role of firms in intergenerational mobility. *Working paper, CEMFI.*

Appendices

A Additional tables

Table A.1: Descriptive statistics of estimation samples

	All Contracts	First Job	Further Jobs	Mass layoffs
Wage	6.02	5.91	6.14	6.07
Worker FE	-0.13	-0.14	-0.13	-0.13
Firm FE	3.05	3.03	3.08	3.05
Cov. FE	0.26	0.34	0.19	0.29
Covariates	3.09	3.02	3.19	3.16
Background	82.71	82.97	82.43	83.83
STEM	25.26	28.62	25.79	22.10
Master	53.43	53.74	53.10	52.27
Grade	51.65	53.35	49.83	48.39
Male	41.06	41.79	40.28	35.81
Year of birth	1970-1998	1970-1998	1970-1998	1971-1997
Year	2005-2021	2005-2021	2006-2021	2006-2021

Notes: The upper part shows the averages of the variables from INPS, and the bottom part the averages of the variables from UNIMORE.

B Full model results of subsample estimations

Table B.1: Results - First jobs

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.0407***	0.0182***	0.0326***	-0.101***	-0.00362	-0.00654
	(0.00844)	(0.00309)	(0.00375)	(0.0270)	(0.00296)	(0.00567)
STEM	0.0479***	0.0629***	0.0132***	-0.0214	-0.00138	-0.0267***
	(0.00688)	(0.00298)	(0.00302)	(0.0233)	(0.00291)	(0.00503)
Master	0.0331***	0.00430*	-0.0126***	-0.150***	0.00507**	0.0363***
	(0.00634)	(0.00248)	(0.00288)	(0.0203)	(0.00256)	(0.00464)
Grade	0.102***	0.0388***	0.0407***	-0.113***	0.00240	0.0201***
	(0.00595)	(0.00244)	(0.00266)	(0.0194)	(0.00246)	(0.00439)
Male	0.0824***	0.0813***	0.0519***	-0.0216	-0.00335	-0.0475***
	(0.00633)	(0.00264)	(0.00284)	(0.0207)	(0.00264)	(0.00465)
Constant	6.216***	0.0441	3.053***	0.504***	-0.00735	3.126***
	(0.0513)	(0.0377)	(0.0184)	(0.153)	(0.0323)	(0.0536)
Year FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Observations	39,009	39,009	39,009	39,009	39,009	39,009
R-squared	0.120	0.242	0.097	0.040	0.001	0.065

Notes: Robust standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.2: Results - Further jobs

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.0688***	0.0231***	0.0350***	-0.0423*	-0.000637	0.0114*
	(0.00797)	(0.00344)	(0.00375)	(0.0253)	(0.00398)	(0.00630)
STEM	0.109***	0.0666***	0.0306***	0.0733***	-0.00177	0.0138**
	(0.00671)	(0.00325)	(0.00296)	(0.0198)	(0.00401)	(0.00604)
Master	-0.0476***	0.000828	-0.0409***	-0.0530***	0.00356	-0.0111**
	(0.00596)	(0.00270)	(0.00273)	(0.0174)	(0.00327)	(0.00506)
Grade	0.0954***	0.0399***	0.0315***	-0.0496***	0.00146	0.0226***
	(0.00564)	(0.00264)	(0.00258)	(0.0162)	(0.00323)	(0.00493)
Male	0.140***	0.0871***	0.0592***	0.0464***	-0.00464	-0.00183
	(0.00624)	(0.00288)	(0.00281)	(0.0177)	(0.00357)	(0.00547)
Constant	6.243***	0.0522	3.077***	0.547***	-0.0775	3.191***
	(0.119)	(0.0736)	(0.0236)	(0.196)	(0.111)	(0.176)
Year FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Observations	31,025	31,025	31,025	31,025	31,025	31,025
R-squared	0.165	0.281	0.086	0.013	0.003	0.073

Notes: Robust standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.3: Results - Mass layoffs

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.106***	0.0265***	0.0539***	-0.107	-0.0133	0.0392**
	(0.0239)	(0.00797)	(0.0105)	(0.0754)	(0.00944)	(0.0170)
STEM	0.0726***	0.0614***	0.0262***	0.149**	-0.00356	-0.0114
	(0.0204)	(0.00794)	(0.00859)	(0.0623)	(0.00993)	(0.0166)
Master	-0.0570***	-0.00166	-0.0242***	-0.0903*	-0.00444	-0.0267**
	(0.0155)	(0.00588)	(0.00692)	(0.0465)	(0.00745)	(0.0129)
Grade	0.0898***	0.0373***	0.0262***	-0.0550	-0.00849	0.0347***
	(0.0148)	(0.00593)	(0.00663)	(0.0445)	(0.00756)	(0.0125)
Male	0.142***	0.100***	0.0372***	0.0593	-0.000593	0.00514
	(0.0174)	(0.00669)	(0.00744)	(0.0507)	(0.00889)	(0.0148)
Constant	6.367***	0.0340	3.068***	0.585	0.115	3.150***
	(0.232)	(0.115)	(0.0328)	(0.455)	(0.0758)	(0.153)
Year FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Observations	5,621	5,621	5,621	5,621	5,621	5,621
R-squared	0.175	0.316	0.102	0.038	0.009	0.062

Notes: Robust standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.