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Background wage premia, beyond education: firm sorting and unobserved abilities

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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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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) and technological changes (Arntz et al., 2025). In this paper, we want to test the extent to which firm premiums can also help to explain the intergenerational dimension of inequality. In particular, we want 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). The exploration of these further transmission factors lies at the intersection of sociological and economic aspects. From the economics perspective, Agnarsson and Carlin (2002) has 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, which 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 failures, where economic relationships are deeply embedded in social contexts, enabling quicker and more reliable exchanges of information and trust within established networks (Magruder, 2010; Bavaro and Patriarca, 2022). 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 (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.

The idea of this paper is to employ an 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 favorable or less favorable compensation structures; channels that emerge as a result of forms of market imperfections.

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 north-east of Italy. By focusing on this specific institution and utilizing 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 on graduation day, featuring students tossing their caps in celebration. While 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 studies on the impact of firm-specific differences on wage inequality.

Our findings indicate that the economic background of parents significantly influences the allocation of workers to firms with varying wage policies. This parental background effect on wages results as substantial and relatively higher than the one mediated by worker individual characteristics. We will delve deeply into the themes that ultimately shape our findings. Specifically, we will explore how this background effect evolves as individuals transition from initial jobs to later positions, showing a cumulative effect, and then investigate how these factors impact the sorting between firms and worker types, with a particular focus on understanding the mechanisms behind the observed disparities.

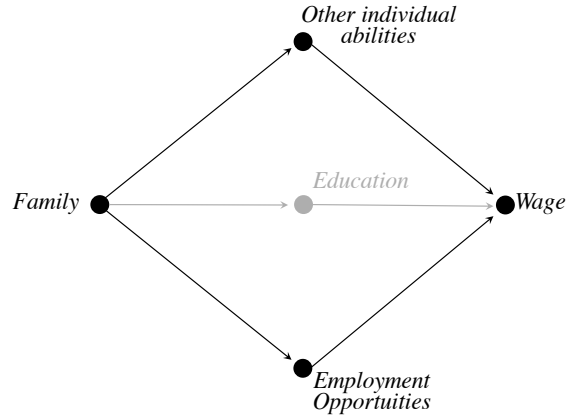
The structure of this paper is as follows. Section 2 outlines the conceptual framework, which underpins both our econometric strategy and our data selection approach, discussed further in Section 3. Section 4 details the methodology employed in our analysis, while Section 5 presents the results of the econometric analysis, including a robustness check for our identification hypothesis. 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.

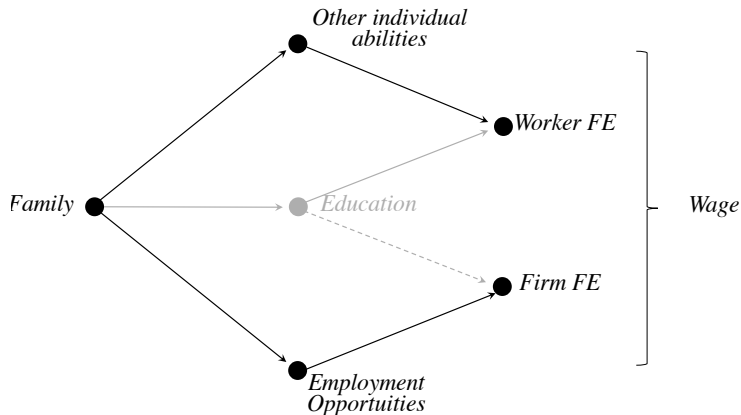
Figure 1: The channels of influence of background on wages 1



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 drowned it in gray since 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.

Figure 2: The channels of influence of background on wages 2



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 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 lays on the background outside the analysis. Unlike the case of education, which we can consider acting on both wage components, the central step for the purposes of 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 first 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. Table 1 presents descriptive statistics for the variables extracted from the Uniemens dataset. In the first column we report the full Uniemens 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 sect 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 Uniemens, 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.

Table 1: Descriptive statistics - Background variables

	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
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 workers in the UNIMORE dataset.

3.2. *Unimore data*

We consider all graduates from the University since 2005. The fourth column in Table 1 shows the same variables used in the first stage estimation for the sample of the match between the two data sources. As expected, the comparison between the third and the fourth columns highlights the differences between a sample limited to young individuals and a sample limited to young graduates. Accordingly, while the average age of workers in our analysis is almost equal to that of the entire sample restricted to ages 23-35, their tenure is shorter (almost 8 years compared to 9 years), as they enter the labor market later than non-graduated workers. At the same time, wages are higher, and the occupational composition is characterized by a higher share of white-collar workers and a greater presence in lower-level occupations. Additionally, the share of males is lower (42 percent versus 57 percent), since university students are predominantly female. Finally, the table indicates that we rely on data from slightly more than 39,000 workers, repeated over 223,500 times. The number of firms included in our analysis is more than 24,500.

As to the information that we obtain from the Unimoredata dataset, 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 household economic background. This latter variable is a dummy indicating whether the student was exempted from paying university fees in the first year of enrollment. Specifically, this exemption is determined by a means test mechanism based on both income and family wealth (ISEE), which is periodically updated for inflation. In 2022, this indicator corresponded, in the absence of family wealth, to a total yearly income of 24,500 euros. The means test mechanism ensures that the exemption is given to students whose families have limited financial resources, thus providing a clear indicator of economic background. To measure the background in the increasing direction, the corresponding dummy variable takes the value 0 if the student has a means-tested exemption and 1 otherwise.

The descriptives are shown separately according to the two different observational levels of the matched databases: individual yearly observations in Uniemens and individuals in Unimore, from which the reported variables originally come. In this unit of analysis, slightly more than four out of five contracts are associated with individuals from a higher economic background. In the sample of all observations, this share is higher, anticipating evidence that will be discussed below, i.e., the positive association between

Table 2: Descriptive statistics - means of Unimore variables

	Matched observations	Graduates
Background	85.61	82.97
STEM	27.60	28.62
Master	55.02	53.74
Grade	53.34	53.35
Male	41.80	41.79
Year of birth	1970-1998	1970-1998

Notes: The first column shows averages on the INPS sample, the second column considers the subsample on which the AKM estimation is performed, and the third column is on the subsample UNIMORE.

economic background and contract duration. Students who graduated in STEM (Science, Technology, Engineering, and Mathematics) fields make up around one-fourth of the sample. We also have information on the relative GPA, indicating whether it is higher than the average of their respective study programs in the same graduation cohort. Master’s degrees account for more than half of the sample. In the estimation, we will also consider the contract level and other sample restrictions. The corresponding descriptives are reported in Table A.7 in Appendix.

4. Methodology

Our methodology exploits a two stages approach in the same way as in [Bana et al. \(2023\)](#) and [Eliason et al. \(2023\)](#), that use in the second step the firm and worker fixed effects estimated according to the methodology proposed by [Abowd et al. \(1999\)](#). [Eliason et al. \(2023\)](#) use this estimation to analyze 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, conditioned to education and among graduates. We estimate worker fixed effects and firm-specific wage premia of Italian firms and workers. We then investigate the relationship between these two distinct components of wages with workers’ parental background.

In the case study we consider, we analyze graduates from an Italian university, thus focusing on a 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. Specifically, we aim to disentangle the residual background premium into two different parts: unobserved skills and sorting among differently paying firms.

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 premiums from the equation:

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

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 as worker wage premiums 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 premiums 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. Given the importance of worker mobility in identifying firm fixed effects, we focus on the largest firms-workers connected set, following the approach outlined by Abowd et al. (2002). By restricting our analysis to this set, we concentrate on 99% of the observations in our panel.

Done all this, we proceed with the estimation of equation (1) as in Abowd et al. (2002) ending up with so-called firm premiums 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 premiums common to all workers employed at that firm. Another potential concern related to the estimation of firm premiums 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 the next section.

4.2. Analysis of the background premium

Together with log wages, the decomposition of wages obtained in the first level estimation is used in the second stage as we build four OLS models with four different dependent variables to analyze the impact of workers' family background characteristics.

The estimated equations are all specified as follows:

$$y_{ijt} = \gamma Z_{ijt} + \delta C_i + \zeta_{ijt} \quad (2)$$

where y_{ijt} are log real weekly wages and 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 model (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 worker fixed effects θ_i shows the component of the background channels that impact individual fixed effects, that is, wage premia that are related to individual productive abilities. The coefficient 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 premia 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.

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

The decomposition methodology and its identification hypotheses do not exclude firm-worker type sorting, which is instead an issue in the AKM literature. An unbiased estimation of the sorting effects would involve a deeper insight by correcting with leave-out estimators or similar finer analysis (Kline et al., 2020). The debate in the literature is on the magnitude rather than on the sign of the correlation between the two effects, which is positive. In our analysis, we are mainly interested in the direction of the effect of the background than in the magnitude, thus we will not delve deeper, considering also that the correlation we obtain in the general sample is in line with other analyses on the same or similar data (Macis and Schivardi, 2016; Casarico and Lattanzio, 2024). In this case, the coefficient γ will tell us whether the background channels favor or hinder the positive firm-worker type sorting.

In some estimations, the sample of the analysis includes multiple pieces of information 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 analogous to considering the individual's mean within the sample. Results obtained without weights or directly using individual means are strongly robust, indicating the consistency and reliability of our findings.

The first sample we will consider in the model consists of all firm-worker pairs among our observations, specifically focusing on the wages in the first year of employment. However, career paths in the labor market can vary significantly, and this is particularly true for the entry of young people. In our case, we observe individuals aged 23 to 35 years. By focusing on the first year of employment, we aim to capture the initial impact of educational background and family economic status on entry-level wages. This approach allows us to analyze how these factors influence early career outcomes and provides a baseline for understanding longer-term career progression. Given the age range of our sample, we can explore how the transition from education to the labor market unfolds for young adults, shedding light on the variability in career paths during these formative years. Initially, we focus on analyzing the wages and characteristics associated with these first jobs. After this, we shift our analysis to subsequent jobs. We begin by examining all further jobs to understand the broader career trajectories and wage developments. Then, we narrow our focus to a specific subset: workers who have moved from a previous firm due to a mass lay-off. This restriction allows us to analyze the impact of involuntary job changes on career paths and wage outcomes. We

define a mass lay-off as a situation where a firm reduces its workforce by more than 30%. This identification approach is commonly used in the literature (see [Eliason et al. 2023](#), among others) to consider workers who are seeking new employment under similar conditions, as was in the previous case when we considered entry jobs. To explore the main findings further, we stratify by individual and firm-level variables. Then we consider the characteristics of the matches in terms of contract features, estimating the same model as in(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, in the search for 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 prior to 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](#) 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 premiums before and after a move (here proxied by coworker wages) would not represent firm wage premiums 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

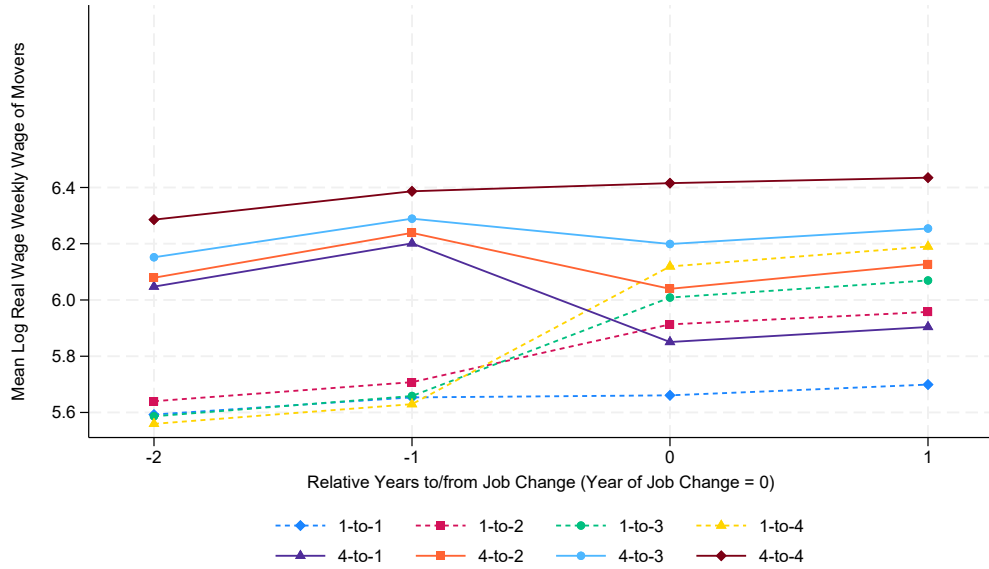


Figure 3: Mean weekly earnings of movers across quartiles of average coworker weekly earnings. Data relate to 2005-2021 period.

were the case an "Ashenfelter dip" would appear. The same line of reasoning could apply to shocks on 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 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 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 the model (1) on the larger connected set. The main output of the estimations for the matched samples is reported in the last three rows in table 2 above. The correlation between workers' and firms' effects is positive 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](#)).

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

	All sample	Largest Connected set
<i>Sample size</i>		
Workers	23,832,141	23,388,179
Firms	3,847,348	3,486,907
<i>Summary Statistics</i>		
Observations	218,797,977	215,846,510
Mean log wages	6,116	6,119
Standard deviation of log wage	0,447	0,448
<i>Summary of estimates</i>		
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

5. Results

After estimating worker and firm fixed effects for Italian workers and firms, we match these data with our sample of graduates to focus on analyzing the residual background premium. As previously mentioned, we will begin by considering all contracts and then examine subsamples corresponding to different phases of the labor market path.

5.1. The residual background premia

We start by examining the estimation of the model (2) on all the job matches in the sample. Results are shown in Table 4. The first column of the 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, indicating that even among individuals with identical 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 roughly corresponding to the first quintile of family economic conditions.

The next two columns report the results of the estimations that consider as dependent variables the wage components estimated in the first stage as two-way fixed effects, which are the main focus of our analysis. Both of

Table 4: Results - All contracts

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.0535*** (0.00616)	0.0187*** (0.00267)	0.0347*** (0.00276)	-0.0509*** (0.0176)	-0.0035 (0.00225)	0.00365 (0.00405)
STEM	0.0665*** (0.00515)	0.0608*** (0.00263)	0.0199*** (0.00225)	0.0671*** (0.0160)	-0.0013 (0.00229)	-0.0128*** (0.00379)
Master	0.00388 (0.00437)	0.00858*** (0.00210)	-0.0283*** (0.00203)	-0.0870*** (0.0130)	0.00494** (0.00193)	0.0186*** (0.00323)
Grade	0.0921*** (0.00429)	0.0388*** (0.00212)	0.0340*** (0.00195)	-0.141 (0.0130)	0.00244 (0.00192)	0.0168*** (0.00320)
Male	0.0990*** (0.00464)	0.0799*** (0.00229)	0.0563*** (0.00211)	0.0889*** (0.0140)	-0.00338* (0.00205)	-0.0339*** (0.00343)
Constant	6.280*** (0.0508)	0.0429 (0.0377)	3.058*** (0.0181)	0.444*** (0.144)	-0.00743 (0.0322)	3.115*** (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: The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. STEM is equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students. 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. We always control for year and cohort-fixed effects. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 significantly shapes individual abilities, beyond the educational channel, the impact is more pronounced through the opportunities provided by employment in firms with different wage policies.

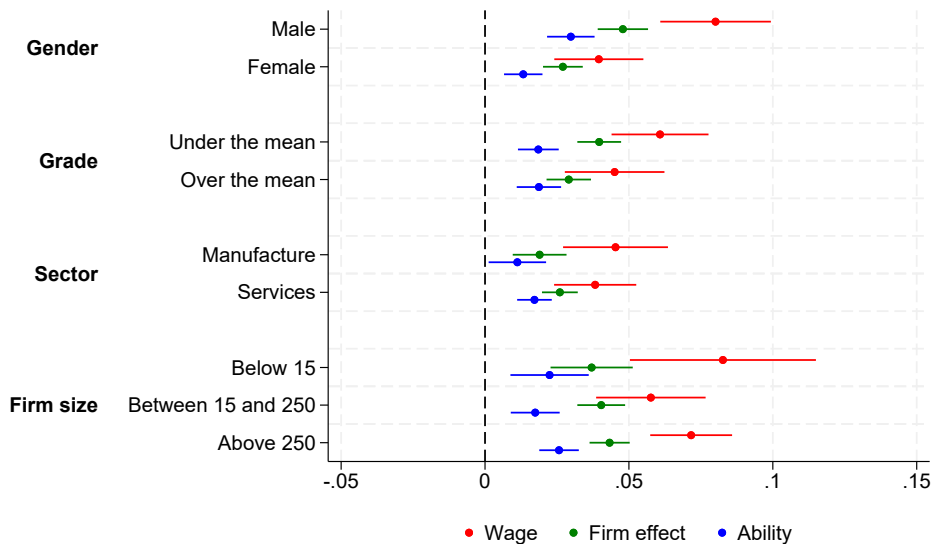
The fourth column shows the coefficients related to the correlation between the two effects. In both the overall Italian national sample and the matched sample from Unimore, the correlation between the two effects is positive, indicating a positive sorting effect between firms and worker types. When considering this correlation as the dependent variable, the background variable shows a negative coefficient. For graduates coming from better economic backgrounds, the firm-worker type matching is worse. If better matching between firms and workers corresponds to efficiency effects, the channels

related to family background demonstrate a controversial effect.

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. This indicates a lack of correlation between first-job wages and the first-stage covariates. Control variables exhibit the expected signs, showing a wage premium for STEM fields, higher levels of education, higher GPAs, and male gender.

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. Regarding the firm-level characteristics, we consider broad sectors and the firm’s employment dimension.

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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 overall background premium for women. This suggests that gender disparities in the labor market are influenced by both the types of firms that employ women and the perceived or actual abilities of the women themselves. 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 premiums between sectors and firm sizes, these differences are not substantial enough to significantly alter the general conclusions. This suggests that the mechanisms of wage determination through family background and firm characteristics remain consistently influential across different firm types and sectors.

5.2. The path in the labor market

In the main analysis, we have considered all contracts in the matched sample. Since the analysis concerns individuals up to the age of 35, and given the variety of transition paths from education to the labor market, by taking all observed contracts together, we have pooled different phases of the workers' careers. In these different phases, the background channels may act non-uniformly. In this section, we delve deeper into the labor market paths of graduates by considering alternative sample restrictions. These restrictions allow us to study individuals under similar conditions in the face of the labor market, thereby identifying the background effect under more specific and

comparable circumstances. By segmenting the data this way, we can gain a clearer understanding of how family background influences career outcomes at different stages of professional development, providing more nuanced insights into the interplay between education, background, and labor market dynamics.

Table 5 summarize these main paths. To ease the comparison, the first row repeats the benchmark coefficients of the variable of interest shown in Table 4. In the second row, we report the estimation of the same model, as in equation 2, considering only the first jobs observed for each individual. The background premium on first jobs is partially lower than on all contracts. The coefficient on worker fixed effects is substantially the same since both refer to the variance of 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 vary between the samples. 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. This suggests that, at the beginning of their careers, graduates may experience less variation in wage outcomes related to the specific firms they join. Instead, the impact of family background may manifest more strongly later in their careers, when firm-specific wage policies and career progression opportunities become more pronounced. Additionally, the coefficient on the fixed effects covariance remains substantially the same as in the main sample. This consistency indicates that the relationship between worker and firm fixed effects does not significantly change when focusing solely on first jobs.

We now shift from the analysis of first jobs to what happens beyond labor market entry. The third row reports the estimation of all job transitions, i.e., relative to job changes from year to year. 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. This indicates that factors specific to job transitions and the particular matches between workers and firms play a crucial role in determining wage outcomes as individuals move through their careers. The evidence in the analysis in the next section will confirm such a hypothesis.

Next, to consider individuals in similar circumstances in the labor market

beyond their first contracts, we restrict the sample to firm changes that occurred from firms experiencing significant lay-off episodes in the year of job interruption, defined as a decrease in firm employment by more than 30%, in a similar fashion as in [Eliason et al. \(2023\)](#). In the bottom section of Table 5, we report the estimation of wages of the new job after such changes. Although this approach limits the analysis to a specific scenario, it provides insight into the background effect when transitions are not workers' choices. This restriction allows us to examine how graduates from different backgrounds fare when they are forced to change jobs due to significant layoffs. The results show that 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 individuals from better economic backgrounds may be better equipped to secure favorable positions even in adverse job market conditions.

Again, the coefficients of the two fixed effects components move less, though in the same direction as the overall premium, particularly the firm component, which increases up to 5.4%. The component of the covariates from the first stage is significant, as observed in the more general case for all job changes mentioned above.

Nonetheless, focusing back on the two channels of background influences under scrutiny, the estimation of further jobs confirms the general evidence robustly. Additionally, it highlights the reinforcement of the background premium through the labor market path, consistent with the progressive increase in the overall background premium.

This finding indicates that the impact of family background not only persists but also intensifies as individuals progress in their careers. The firm-specific component plays a significant role, suggesting that as workers move between jobs, the advantages conferred by a better economic background become more pronounced, particularly in securing positions in firms with higher wage premiums.

The evidence presented so far confirms the significant role of family circumstances in shaping career paths within the labor market, including the likelihood of being selected by higher-paying firms. Given the importance of firm characteristics, it is also plausible to consider that wage policies are connected to qualitative aspects of employment within the firm. Therefore, we decided to delve into aspects related to job types, particularly the nature of the contract and working hours for graduates in their first job. Examining the nature of the contract and working hours provides insight into the

Table 5: Results - The path in the labor market

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

Notes: The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. STEM is equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students. 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. We always control for year and cohort-fixed effects. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Complete results of the regressions are shown in Table 4 and in Tables A.8, A.9, A.10 in Appendix.

quality and stability of employment that graduates secure at the beginning of their careers. It is essential to understand whether individuals from more advantaged backgrounds are more likely to obtain permanent contracts and full-time positions, which offer greater job security and benefits. By analyzing these aspects, we can further elucidate the mechanisms through which family background influences early career outcomes and long-term professional trajectories.

Considering the estimates in the first two columns of Table 6, we report the coefficient estimates of background variables in models that have 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. Thus, the influence of background extends beyond wage aspects to encompass job quality.

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. This indicates that individuals from more advantaged family backgrounds are not only more likely to obtain better-quality jobs initially but also more likely to maintain stable employment over time.

Finally, the increase in background effects beyond the first jobs suggests exploring potential mechanisms that persist over time and amplify the effects of background. To this end, we analyse the probability of individuals moving to a firm with higher fixed effects than their previous one by considering only the sample of those who change firms from one year to the next. The sign and the value of the coefficient confirm that the selection mechanism among firms remains and strengthens in career paths within the labor market. These findings indicate that family background continues to play a significant role throughout an individual’s career, influencing not only initial job quality but also the trajectory of job mobility and stability. The increase in background effects for successive jobs suggests that there may be mechanisms that persist over time and amplify the effects of background. To investigate this, 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 confirm that the selection mechanism among firms remains and strengthens in career paths within the labor market. These findings suggest that family background continues to play a significant role throughout an individual’s career, influencing not only initial job quality but also the trajectory of job mobility and stability.

6. Conclusions

This paper has explored 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 whose finer information on education has been matched, together with a reliable proxy of family economic conditions, to the employer-employee database of the Italian labor market. In line with the literature ([Lam and Schoeni, 1993](#)), the general evidence shows that family background plays a significant role in determining wage premiums 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 quality, level, and typology of education attained, the wage differences among graduates are still large and strongly related to family backgrounds. In the case of the main variable considered, that is, belonging or not to the bottom 20% of the distribution

Table 6: Results - Alternative outcomes on all contracts

	Full time	Permanent	Change firm	Better firm
Background	0.0554*** (0.00482)	0.0622*** (0.00544)	-0.0398*** (0.00346)	0.0251*** (0.00866)
STEM	0.0725*** (0.00364)	0.0665*** (0.00468)	-0.00644** (0.00262)	0.0414*** (0.00776)
Master	-0.0491*** (0.00358)	-0.00444 (0.00421)	-0.00498*** (0.00231)	-0.0265*** (0.00670)
Grade	0.0356*** (0.00347)	0.0438*** (0.00408)	-0.0282*** (0.00226)	0.00489 (0.00655)
Male	0.133*** (0.00355)	0.0813*** (0.00436)	-0.0022 (0.00240)	0.0403*** (0.00707)
Constant	0.740*** (0.0328)	0.746*** (0.0330)	0.180*** (0.0284)	0.443*** (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 the job matches in the sample. Change firm relies on the matched sample, excluding the initial jobs. Better firm considers the subsample of workers who have changed firm. The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. STEM is equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students. 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. We always control for year and cohort-fixed effects. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of family earning capacity, the correspondent wage premium accounts for 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, with the predominance of the firm-level channel remaining consistent in all subsamples. The background effect increases along the labor market path when graduates move from first jobs to subsequent positions. The effect due to selection among firms grows with the transition to later jobs. Additionally, background positively influences

the probability that a job change will lead to employment in a firm with better-fixed effects. Conversely, disadvantaged background reduce the likelihood of staying with the same firm. The stratified sample analyses confirm the robustness of the results. The case of gender differences stands out, confirming that a significant portion of the wage gender gap is due to firm effects (Casarico and Lattanzio, 2024). It also shows that the background channels are weaker in this case, although still significant and with the same relative importance.

There are many possible interpretations of the firm sorting 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 on the transition from mass lay-offs. 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 better matching between firms and workers corresponds to efficiency effects, 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 (both formal and informal), 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 premiums 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.

Social security policies 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. Labor policies, such as implementing generic training programs, can help reduce the monopsonistic power of employers by enhancing worker skills and employability, thus increasing their bargaining power. Work orientation policies can guide individuals through the complexities of the labor market, helping them make informed career choices and improving their chances of securing quality employment.

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Appendix A. Appendix

Table A.7: Descriptive statistics

	First Job	First Contracts no First Job	Mass Lay-offs
Back eco	82.97	82.43	83.83
STEM	28.62	25.79	22.10
Master	53.74	53.10	52.27
Grade	53.35	49.83	48.39
Male	41.79	40.28	35.81
Year of birth	1986.71	1985.96	1985.23
Year	2012.63	2014.99	2014.48
Wage	5.91	6.14	6.07
Worker FE	-0.14	-0.13	-0.13
Firm FE	3.03	3.08	3.05
Cov. FE	0.34	0.19	0.29
Covariates	3.02	3.19	3.16

Notes: The first column shows averages on the sample of workers' first job, the second column considers the sample of all the first contracts but excludes the first job, the third column refers to the dataset on mass lay-offs

Table A.8: Results - First job

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.0407*** (0.00844)	0.0182*** (0.00309)	0.0326*** (0.00375)	-0.101*** (0.0270)	-0.00362 (0.00296)	-0.00654 (0.00567)
STEM	0.0479*** (0.00688)	0.0629*** (0.00298)	0.0132*** (0.00302)	-0.0214 (0.0233)	-0.00138 (0.00291)	-0.0267*** (0.00503)
Master	0.0331*** (0.00634)	0.00430* (0.00248)	-0.0126*** (0.00288)	-0.150*** (0.0203)	0.00507** (0.00256)	0.0363*** (0.00464)
Grade	0.102*** (0.00595)	0.0388*** (0.00244)	0.0407*** (0.00266)	-0.113*** (0.0194)	0.00240 (0.00246)	0.0201*** (0.00439)
Male	0.0824*** (0.00633)	0.0813*** (0.00264)	0.0519*** (0.00284)	-0.0216 (0.0207)	-0.00335 (0.00264)	-0.0475*** (0.00465)
Constant	6.216*** (0.0513)	0.0441 (0.0377)	3.053*** (0.0184)	0.504*** (0.153)	-0.00735 (0.0323)	3.126*** (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: The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. STEM is equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students. 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. We always control for year and cohort-fixed effects. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Results - Mass-layoffs

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.106*** (0.0239)	0.0265*** (0.00797)	0.0539*** (0.0105)	-0.107 (0.0754)	-0.0133 (0.00944)	0.0392** (0.0170)
STEM	0.0726*** (0.0204)	0.0614*** (0.00794)	0.0262*** (0.00859)	0.149** (0.0623)	-0.00356 (0.00993)	-0.0114 (0.0166)
Master	-0.0570*** (0.0155)	-0.00166 (0.00588)	-0.0242*** (0.00692)	-0.0903* (0.0465)	-0.00444 (0.00745)	-0.0267** (0.0129)
Grade	0.0898*** (0.0148)	0.0373*** (0.00593)	0.0262*** (0.00663)	-0.0550 (0.0445)	-0.00849 (0.00756)	0.0347*** (0.0125)
Male	0.142*** (0.0174)	0.100*** (0.00669)	0.0372*** (0.00744)	0.0593 (0.0507)	-0.000593 (0.00889)	0.00514 (0.0148)
Constant	6.367*** (0.232)	0.0340 (0.115)	3.068*** (0.0328)	0.585 (0.455)	0.115 (0.0758)	3.150*** (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: The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. STEM is equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students. 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. We always control for year and cohort fixed effects. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Results - Further jobs

	Wage	Worker FE	Firm FE	Cov. FE	Residual	Covariates
Background	0.0688*** (0.00797)	0.0231*** (0.00344)	0.0350*** (0.00375)	-0.0423* (0.0253)	-0.000637 (0.00398)	0.0114* (0.00630)
STEM	0.109*** (0.00671)	0.0666*** (0.00325)	0.0306*** (0.00296)	0.0733*** (0.0198)	-0.00177 (0.00401)	0.0138** (0.00604)
Master	-0.0476*** (0.00596)	0.000828 (0.00270)	-0.0409*** (0.00273)	-0.0530*** (0.0174)	0.00356 (0.00327)	-0.0111** (0.00506)
Grade	0.0954*** (0.00564)	0.0399*** (0.00264)	0.0315*** (0.00258)	-0.0496*** (0.0162)	0.00146 (0.00323)	0.0226*** (0.00493)
Male	0.140*** (0.00624)	0.0871*** (0.00288)	0.0592*** (0.00281)	0.0464*** (0.0177)	-0.00464 (0.00357)	-0.00183 (0.00547)
Constant	6.243*** (0.119)	0.0522 (0.0736)	3.077*** (0.0236)	0.547*** (0.196)	-0.0775 (0.111)	3.191*** (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: The variable of interest Background is equal to zero if the student has a means-tested exemption and one otherwise. STEM is equal to one for students who graduated in Science, Technology, Engineering, or Mathematics. Master is equal to one for master students. 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. We always control for year and cohort-fixed effects. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.