Same Firm, Different Wage Premium:

An Investigation of Firm Fixed Effects at the Occupational Level

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Abstract: A long-standing line of literature in labor economics recognizes that workers with similar characteristics and skills earn different wages in different firms. In a decentralized economy, where the wage setting power is at the firm-level, these differentials are ascribed to firm-specific pay policies, hence the "firm wage premium." Growing availability of matched employer-employee data eases investigating the role of heterogeneity in firm wage premia in the evolution of wage inequality. In this paper, I allow firms to set differential wage policies to different occupational classes, i.e. managers, blue collars, and white collars. Using administrative data from the Veneto region in Italy, I show that (a) within the same firm, different occupations receive different firm premia so that the high-type firms are not "equally good" for all their employees. Ranking employers by the occupation-specific firm fixed effects reveals substantial heterogeneity in the wage policies applied to the different occupational groups within the same firm. Specifically, I show that (b) the highest-paying firms for a given occupational group are likely to be among the most discriminatory for the other employees. Eventually, examining the evolution of occupation-specific firm policies over two decades, this paper provides empirical evidence that (c) within-firm wage differentials between white and blue collars increased among Veneto employers in the 1990s with respect to the 80s.

Keywords: AKM, firm premium, occupations, Veneto

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1 Introduction

A long tradition in the economic literature establishes that workers with similar skills earn different wages when employed in different firms [Slichter, 1950, Krueger and Summers, 1988, Van Reenen, 1996]. In this sense, each firm applies a specific wage policy to its employees, determining employer-specific wage differentials independent of observed and unobserved worker characteristics.

While persistent wage premia are at odds with competitive labor markets in which wage levels are taken as given by firms, Card [2022] surveys four main empirical findings suggesting why employer wage-setting power is non-negligible: evidence on quit and recruiting responses to wages; evidence on the relationship between wages and firm productivity; evidence on the concentration of employment in small numbers of employers; and evidence of conspiracies and other forms of firm behavior targeted at suppressing firm-to-firm mobility and wage growth.

Abowd et al. [1999] (henceforth AKM), Goux and Maurin [1999], and Abowd et al. [2002] first propose an econometric model for the identification of firm premia as determinants of labor earnings, once differences in observed and unobserved characteristics of workers are controlled for. Subsequently, several papers show the existence of substantial heterogeneity in firm pay policies and that it contributes to the rise in earnings inequality in different countries since the 1990s [Card et al., 2013, Mueller et al., 2017, Devicienti et al., 2019, Song et al., 2019].

It is important to note that all these aforementioned studies implicitly assume that, within a firm, the same wage policy applies to all employees. The first to deviate from this assumption is Card et al. [2016]: they show that firms apply different wage policies to male and female employees with women receiving only 90% of the firm-specific pay premia earned by men.[1] Kline et al. [2020] estimate age-specific firm wage premia and reject the hypothesis that older and younger workers face exactly the same vectors of firm effects.

In this paper I propose a new perspective on workplace heterogeneity, relaxing the implicit assumption of a unique premium distributed to all employees within a firm and allowing employers to set differential wage policies to different occupational classes, i.e. managers, blue collars, and white collars. To do so, I use administrative data covering the entire population of private-sector workers and firms in the Italian region of Veneto and estimate separate AKM models for managers, white collars, and blue collars in order to retrieve *occupation-specific* firm wage premia.[2] I then compare these estimates across occupational

[1] Similar results are found in Bruns [2019] and Casarico and Lattanzio [2019].

[2] Torres et al. [2018] apply a three-way fixed effects accounting for worker, firm, and job title fixed effects, finding that job title fixed effects explain on fifth of wage variance using Portuguese data over a 26-year interval. While such application accounts for the role of heterogeneity between occupations on inequality, it still does not address whether the same firm applies different occupation-specific wage policy.

classes, firms, and time periods seeking to understand the role of firms in shaping inequality between and within occupations.

First, I show that occupation-specific firm pay policies predict well differences in wage levels between firms. Managers, white collars, and blue collars employed in the top 25% of the occupation-specific firm premium distribution earn, respectively, 32%, 40%, and 25% more than workers in the same occupational group employed in firms belonging to the bottom 25%. Such high heterogeneity in pay levels between firms is, however, coupled with great heterogeneity within firms and between occupational classes too. Once I compare the occupation-specific wage policies applied by firms, I observe that the same firm applies different wage policies to its employees depending on their occupation. Specifically, not only does the *level* of the firm premium differs between occupations, but also the *rank* that the same firm occupies along the occupation-specific wage policy distribution. In this sense, for example, the same firm may apply very advantageous wage policies for managers, while being relatively un-rewarding for blue and white collars with respect to the other firms in the market. Overall, I find no correlation between the manager, white collars, and blue collars firm policy distribution suggesting that a high-paying firm for a given occupational class is, therefore, not necessarily as good for the other employees.

This first set of findings provide empirical evidence for a sophisticated wage strategy on the employer's side: while, on average, there exists a clear hierarchy in the returns of the different occupational classes, firms retain a high degree of flexibility in the way in which they remunerate their employees. Such flexibility translates in the possibility on the employer side to increase or reduce the occupational returns of their employees with respect to the market average.

Thus, in a second step, I quantify the gradient of occupation-specific remuneration schemes adopted by firms. To do so, I exploit the fact that, within a (dual) connected set of firms,[3] the AKM occupation-specific firms effects can be directly comparable. In this way, it is possible to rank employers according to degree of discrimination they apply when setting their own occupation-specific policies. For example, in a firm that pays high firm fixed effects to its white collars and low fixed effects to its blue collars, the degree of discrimination will be higher than in a firm that pays similar wage policies to both occupational classes.

I apply regression-based models to identify the returns of the different occupational groups for increasing levels of discrimination applied by firms finding large heterogeneity in the way employers remunerate their employees. For example, in 2001, the latest year of available data in my application, on average, white collars were earning 28.5% more than blue collars, *ceteris paribus*. However, this wage premium

[3]Section 2 provides all the methodological details.

increases to 33.1% among the top 60% most discriminatory firms and to 42.1% in the top 20%. Most notably, my findings show that there is a correlation close to one between the rank of a firm along the occupation-specific fixed effect distribution and its rank along the distribution of firms sorted by increasing wage policy discrimination, meaning that the highest-paying firms for a given occupational group are likely to be among the most discriminatory for the other employees.

Eventually, I study the evolution of occupation-specific firm premia over two decades comparing the 1980s (1982-1991) with the 90s (1992-2001). Results show that, in Veneto region, the returns of white collars on blue collar workers increased by 3 percentage points between the 80s and 90s, passing from 25 to 28%. However, such wage premium increase was larger in firms applying high discrimination policies. Among the top 20% most discriminatory firms, the white collar premium increased by 7 percentage points, passing from 34% to 41%. These findings suggest that firm policy discrimination between occupational classes has increased overtime. As final exercise, I explore whether such changes came together with increased sorting of high-type workers in high-type (occupation-specific) firm policies. To do so, I estimated different measures of sorting proposed by the existing literature [Card et al., 2013, Lopes de Melo, 2018, Kline et al., 2020] for white and blue collars and compare their evolution across time periods. I find that that sorting is increased among blue collars, while it is slightly decreased for white collars. Such patterns might help explaining why white collars returns grew the most among the high-discrimination firms between the 80s and 90s, if, for example, high-type blue collar workforce moved away from high discriminatory firms and were substituted with lower type workers. Once I separate firms in quintiles based on the degree of discrimination applied by firms, however, most of the changes in sorting patterns over time occurred in firms that are at the middle of the distribution. Most notably, among the 20% most discriminatory firms, sorting intensity of both white and blue collars did not change, suggesting that the high increase in white collar return seems not to be correlated with a more effective selection of the labor force by employers.

All together, these findings show that firms applied more discriminatory wage policies over time *independently* from sorting patterns.

To test this hypothesis, I separate firms in quintiles based on the degree of discrimination applied by firms to occupation-specific policies and estimated quintile-specific sorting indexes in the 80s and in the 90s. If the hypothesis was true, I would observe increasing changes in sorting intensity along the quintiles. While I find substantial heterogeneity in sorting intensity between firms, most of the over time changes in sorting patterns occurred in firms that are at the middle of the distribution of firms by discrimination. Most notably, among the 20% most discriminatory firms, sorting intensity of white and blue collars did not change much.

The remainder of the paper is organized as follows: Section 2 discusses the econometric models applied in the paper, Section 3 presents the data, and Section 4 discusses the main results. Section 5 concludes.

2 Methodology

The identification of firm premia requires two-way fixed effect models as first applied by Abowd et al. [1999]. For each worker i, employed in firm j in occupation *Occ(i)* = *Manager*, *White Collar*, *Blue Collar*, in a given year *t=1, ..., T*, I assume the following linear model:

$$w_{it} = \theta_i + \psi_j^{Occ(i)} + X_{it}\beta^{Occ(i)} + \epsilon_{it} \tag{1}$$

where w_{it} is log-daily wage, θ_i is a worker fixed effect representing worker i´s portable earnings component, and $X_{it}\beta^{Occ(i)}$ is a covariate index capturing occupation-specific returns to time-varying characteristics of workers (i.e. age, age squared, and tenure) and firms (i.e. firm size). $\psi_j^{Occ(i)}$ is the occupation-specific firm premium paid to all employees of firm j working in occupation *Occ(i)* during the analyzed period. Unlike simple firm-specific occupational average wages, $\psi_j^{Occ(i)}$ is a persistent earnings component related to firm j and can be interpreted as the wage policy employed in firm j for occupation *Occ(i)*, after controlling for observed and unobserved worker heterogeneity [Devicienti et al., 2019].

With respect to previous literature, I relax the assumption that $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$, allowing the same firm to have different wage policies with its managers, white collars, and blue collars. The identification of these firm effects is possible within a given *connected set* of employers linked by worker mobility [Abowd et al., 2002]. Such a connected set contains all the workers who have ever worked for any of the firms in the group and all the firms at which any of the workers were ever employed. Within each group, all the parameters in equation 1 can be estimated by OLS and *J-1* firm fixed effects, $\psi_j^{Occ(i)}$, will be identified. I perform the analysis on the largest connected groups within the managers, white collars, and blue collars sub-samples separately. While the three sub-samples are mutually exclusive at the individual level, the same firm is not necessarily part of all the three connected set. For this reason, some exercises in the following analysis are conducted on the *triple* connected set, which comprises all those firms connected by worker mobility where I can identify a firm-fixed effect for each occupational class. In Section 4.2, I then focus only one the evolution of the firm wage premia for white and blue collars over time. In this latter case, we refer to the sub-sample including all the firms where both ψ^{WC}

and ψ^{WC} can be estimated as the *double* connected set. Table 1 in Section 3 and Table 5 in Appendix report the details of each working sample used in the analysis.

Estimating firm fixed effects on separated samples by occupational class implies that that firm fixed effects are estimated only by job-movers between different firms and within the same occupation. This means that workers changing firm *and* occupation, do not contribute to the estimation of $\psi_j^{Occ(i)}$. An alternative approach consists in estimating an AKM model where the firm fixed effects are interacted with the occupational class. In this case, $\psi_j^{Occ(i)}$ is estimated over the full connected set, exploiting mobility between both firms *and* occupations. While this latter approach increases overall mobility and, consequently, the resulting connected set will be larger, the estimation of the occupation-specific firm policy $\psi_j^{Occ(i)}$ is derived comparing workers employed potentially in all occupational classes, affecting the interpretation of the wage policy. In this paper, I opt for the most conservative approach and estimate $\psi_j^{Occ(i)}$ based on separated samples by occupation. Nevertheless, I include in the Appendix a replication of the results using the interacted fixed-effect model.

For the model estimates to be unbiased, the error component ϵ_{it} is assumed to not be correlated with any of the elements in θ_i, ψ_j, and X_{it}.[4] This restriction implies that the assignment of workers to firms respects a strict exogeneity condition. This condition rules out the possibility that idiosyncratic shocks in wages might lead to mobility toward a certain type of firm. Card et al. [2013] discuss in detail three forms of endogenous mobility that might bias the identification process and suggest several tests to support the validity of the assumption in the data. Several papers provide evidence in support of the exogenous worker's mobility applying these tests to German data (e.g. Card et al. [2013], Bruns [2019]), to Portuguese data (e.g. Card et al. [2016]), to US data (e.g. Song et al. [2019]), as well as to Italian and Veneto data (e.g. Devicienti et al. [2019], Casarico and Lattanzio [2019], Fanfani [2022], Di Addario et al. [2022]). Nevertheless, in the Appendix, I replicate the exogeneity tests proposed in the literature for the managers, white collars, and blue collars sub-samples, showing that the AKM assumptions also hold in my working sample.

Ensuring the exogeneity of the AKM regression, I can then consistently estimate $\psi_j^{Manager}$, $\psi_j^{WhiteCollar}$, and $\psi_j^{BlueCollar}$. Since my primary focus of interest is understanding whether firms pay different pay premia to different occupational classes, I run occupation-specific AKM models on the triple connected set and normalize the estimated $\psi_j^{Occ(i)}$ to the same (group of) firm(s) in sample ensuring direct comparability between occupation-specific firm wage policies. In Card et al. [2016], the normalization involves the use of balance sheets data where the group of firms with the lowest value-added are used as reference.

[4]Importantly, note that correlation between θ_i, ψ_j, and X_{it} is legit in the model, which allows for sorting of high-skill workers into firms with higher firm fixed effects.

Alternatively, other papers (e.g. Bruns [2019] and Casarico and Lattanzio [2019]) use firms in the food and accommodation sector as reference, assuming no rent-sharing in these sectors. I follow Fanfani [2022] and select the largest firm in terms of employed workers as reference.[5]

I then sort firms based on their rank over the $\psi_j^{Occ(i)}$ distribution. Within the triple connected set, for each firm, I can cross-compare its rank over the distribution of $\psi_j^{Manager}$, $\psi_j^{WhiteCollar}$ and $\psi_j^{BlueCollar}$, thus allowing to test whether the same firm applies different wage policies to their employees depending on their occupation. In this way, it is easy to assess whether high-paying firms for one occupational class (e.g. white collars) are also advantageous for others (e.g. blue collars) with respect to the market.

In the case differences within firms are observed, it is possible to formally estimate the size of the within-firm wage differences between occupational classes. To do so, I adapt the model for the estimation of firm-specific gender gaps proposed by Fanfani [2022] to test within-firm occupational premia. Within both the triple and the double connected set, it is possible to sort employees according to the metric $\mu_j = \psi_j^{WC} - \psi_j^{BC}$, such that the cumulative distribution $F(\mu_j)$ defines quintiles of increasingly more favorable firms for white collars with respect to blue collars. Then, via standard regression methods, I evaluate the marginal effect on wages of being a white collar employed in one of the firms in the right tail of $F(\mu_j)$. Specifically, the model takes the following form:

$$lnw_{it} = b_{wc}1[g = WC] + \sum_{\tau=0.2,0.4,0.6,0.8} b_\tau T_\tau + X_{i,t}\beta + 1[g = WC]X_{i,t}\delta + \omega_j + \rho_i + \epsilon_{it} \tag{2}$$

where w_{it} is the wage of worker i at time t is regressed on a full set of observable individual characteristics, x,[6] accounting for both worker, ρ_i, and firms fixed effects, ω_j.[7] Individual level observable characteristics are interacted with the occupational dummy $1[g = WC]$ distinguishing white from blue collars. The coefficients of interests are the b_τ, which are associated with a given quintile τ of the worker i's employer along the cumulative distribution $F(\mu_j)$. Formally:

$$T_\tau = 1[g = WC]1[\tau + 0.2 \geq F(\mu_j) > \tau] \tag{3}$$

$$\mu_j = \psi_j^{WC} - \psi_j^{BC} \tag{4}$$

b_τ can be interpreted as the marginal effects on white collars' wages of working in a firm at the τ

[5]Results applying different normalization strategies deliver comparable results.
[6]We control for age, age squared, tenure and a full set of year fixed effects
[7]In this exercise firm fixed effects are common to both white and blue collars.

quintile of the distribution of μ_j, with respect to being employed in a firm that applies the most favorable blue collars wage policies with respect to the white collars one. In this sense, b_τ measures the additional wage premia that white collars gain if employed in firms that have increasingly divergent wage policies for white with respect to blue collars, *ceteris paribus*. The aim of the exercises is, therefore, to quantify the gradient of wage differences between occupational classes applied by firms and can be seen as a test on the relevance of occupation-specific AKMs in ranking employers wage policies. Note that the same exercises can be done for any pair of occupational classes within the TCS. Therefore, it is possible to estimate within-firm wage differences between managers and blue or white collars, sorting employees according to the metric $\psi_j^M - \psi_j^{BC}$ and $\psi_j^M - \psi_j^{WC}$, respectively.

It is important to underline that the literature is questioning the AKM regression model. On one hand, new methodologies are proposed to overcome the restrictions on workers' mobility implied by the AKM framework. In particular, Bonhomme et al. [2019] propose a two-step estimation approach that relies on clustering similar firms into groups and then estimating the fixed effects at the cluster level. In their preferred specification, they rely on 10 major clusters. This solves the limited mobility bias and allows for working with bigger working samples since the estimation does not rely on double (or triple) largest connected sets; however, it reduces the heterogeneity of fixed effects from the firm level to the cluster level. On the other hand, Kline et al. [2020] show that the variance of worker- and firm fixed effects estimated via standard AKM models are upward biased. The interpretation of second moments of parameters estimated through AKM can, therefore, be misleading if specific bias correction techniques are not applied.[8] In this regard, it is important to stress, however, that the models proposed in this paper only rely on first moments of the AKM parameters. Consequently, once shown that the exogenous mobility conditions holds for all the occupational classes under analysis, the AKM provides unbiased estimates of occupation-specific firm fixed effects, $\psi_j^{Occ_i}$, which allows for precisely ranking each firm j along the managers, white collars, and blue collars distributions.

3 Data

I rely on the Veneto Workers Histories (VWH) database for all of my estimations. The VWH is a typical matched employer-employee database, where workers can be followed over time and across different employers. It is obtained from the administrative records of the Italian Social Security System and it includes the universe of workers employed in the private-sector in Veneto from 1975 through 2001.[9]

[8] In Appendix C, we show the variance decomposition, with and without bias correction.

[9] See Tattara et al. [2007] for details.

For each year in the sample, the database collects information on the job spells of each worker ever employed in Veneto, providing detailed information on the worker's earnings, job spell length, occupation, contract, age, and gender, all alongside basic information on the employing firm. The VWH also include information on job spells of those workers who moved outside the Veneto region, as long as they remain employed in the private sector.[10] Workers employed in agriculture, public administration, public services (most notable in the health system and railway transportation), and those activities with 1-owner-employer are excluded from the sample. In the VWH, earnings are defined pre-tax, including all in-cash benefits but excluding all in-kind ones. For the estimations, I rely on (log) daily earnings expressed in 2003 euro prices.

The VWH dataset is particularly well suited for the intended analysis for several reasons. First, for each job spell, I can identify the occupational class of each worker, i.e. apprentice, blue collars, white collars, middle-managers,[11] and executives. While these occupational classes are not very detailed, such classification allows for having occupation-specific sub-samples that are large enough for the correct estimation of occupation-specific firm fixed effects as explained in detail in Section 2. Having more granular and specific occupational classification (e.g. ISCO 1 or 2 digit) will drastically reduce the number of same-occupation workers and firms connected by job mobility and, therefore, it will affect the general validity of the results. Secondly, the panel nature of the dataset allows to correctly track worker mobility across firms, tenure, and earnings growth, which are key elements for the correct estimation of worker and firm fixed effects. Finally, Veneto is an important and fairly large region in Italy, representing around 10 percent of the national GDP. It relies on a well-developed manufacturing sector, close-to-natural unemployment rate, and limited out-migration that make it quite comparable to other well-developed Western economies [Devicienti et al., 2019]. For these reasons, the dataset is widely used and its reliability validated by many studies [Card et al., 2014, Bartolucci et al., 2018, Devicienti et al., 2019, Serafinelli, 2019, Kline et al., 2020].

I took several standard steps, in the AKM literature, to define the working sample. First, I selected workers aged 18-64 who are not in their apprenticeship and who are employed for at least four months (16 weeks) in a year. Second, in case of workers with multiple job spells in the same year, I consider only the longest job spell per year in terms of days worked. In case this is not enough to identify unique job spells per year, I kept the observation with the highest weekly earnings. Since our aim is to study

[10] Following Devicienti et al. [2019], I include the universe of job spells available in the estimation sample of the AKM accounting for spells located both inside and outside the Veneto region. This avoids a loss in efficiency due to the exclusion of observable jobs mobility happening in the sample. Nevertheless, all results reported and discussed in the paper are computed considering only firms located in Veneto.

[11] Before 1996 middle-managers, *quadri*, are not distinguishable from white collars.

occupational-specific firm effects, I only consider those firms that employ at least one manager.

In the rest of this paper, I focus primarily on the period between 1996 and 2001. The main reason is that I can only distinguish mid-managers (*quadri*) from white collars after 1996. This choice allows me to have greater support for the estimation of managerial firm fixed effects and reduce variability within the white collars sample refining the estimates. Nevertheless, in Section 4.2, I expand the analysis to the evaluation of occupation-specific firm fixed effects over the long run, estimating separate AKM models for 1982-1991 and 1992-2001.[12]

Table 1 reports main descriptive statistics for the 1996-2001 period. Starting from left, the first three columns describe the largest connected sets within the managers, white collars, and blue collars sub-samples respectively. These three subsets are mutually exclusive since I observe only one job spell per year and in each year a worker can only be classified as a manager (executive or middle-manager), as a white collar, or as a blue collar. The last column on the right depicts the triple connected set (TCS), which comprises all those firms where I can identify a firm-fixed effect for each occupational class. The TCS is, therefore, highly restricted since it comprises all those firms that, within the period of observation, are connected by mobility of both managers, white collars, and blue collars. This involves around 18% of the firms and 59% of the workers of the original working sample. Table 5 in Appendix A provides the main descriptive statistics for the 1982-1991 and 1991-2001 sub-samples.

[12]In this application, I consider managers as white collars and estimated two separated AKM models on the dual connected set of firms linked by white and blue collars mobility. Details are further explained in Section 4.2.

	Largest Connected Stes			**Triple Connected Set**		
	Mangers	*White Collars*	*Blue Collars*	*Mangers*	*White Collars*	*Blue Collars*
Share of women	.11	.44	.3	.095	.44	.31
Average age	45	36	37	45	37	37
Average daily wage (2003 euros)	228	91	64	240	88	65
Avarege Experenice (months)	216	149	154	210	154	156
Share of workers employed in firms with						
Employees <100	.36	.37	.37	.035	.016	.014
Employees 101-200	.11	.14	.17	.047	.029	.024
Employees 201-500	.13	.14	.18	.38	.32	.36
Employees >500	.4	.35	.28	.17	.18	.22
Share of workers employed as						
Manager	.33	.	.	.4	.	.
Mid-manager (*Quadro*)	.67	.	.	.6		.
White Collars	.	1	.	.	1	.
Blue Collars	.	.	1	.	.	1
Share of workers employed in						
Primary Sector	.0023	.006	.0051	.002	.0023	.0014
Secondary Sector	.48	.41	.69	.68	.5	.72
Tertiary Sector	.52	.59	.3	.32	.5	.28
N obs	150.156	1.494.131	1.923.199	85.426	763.919	1.165.771
N workers	42.403	426.222	569.453	24.999	236.419	351.113
N Firms	5.234	10.084	6.983	2.410	2.410	2.410
N workers: % of Overall Sample	.74	.96	.96	.44	.53	.59
N firms: % of Overall Sample	.38	.78	.7	.17	.19	.27

Notes: The sample is Tenure is censored at 1975. Average firms' size is non-weighted and measured by the average of the number of employees working for the company in each year.

Table 1: Descriptive Statics

4 Empirical Results

4.1 Time period 1996-2001

4.1.1 Descriptive Evidence on occupation-specific firm fixed Effects

I begin by estimating equation 1 for each occupational class over the 1996-2001 period. I control for age, age-squared, tenure, and firm size.[13] The details of the AKM model are provided in Appendix XX

First, I want to see weather AKM firm fixed effects predict wage differences between workers employed at different firms type. To do so, after ψ^{Occ} is estimated in the largest connected sets, I report in Table 2 the average daily wages for managers, white collars, and blue collars employed in Veneto by quartiles of the occupation- specific firm fixed effects distribution. Similarly, Figure 1 plots the average (log-)daily wage of managers, white collars, and blue collars employed for subsequent years in firms at different quartiles of the ψ_j^{Occ} distribution over the estimation period of 1996-2001. The figure highlights a clear wage gradient over ψ_j^{Occ} quartiles for all occupational classes where the average worker pay is increasing with ψ_j^{Occ}. Moreover, the wage profiles evolve distinctly and in parallel, thus indicating that workers employed in firms belonging to different ranks of the ψ_j^{Occ} distribution earn substantially different wage *levels* but they do not experience different wage *growth.*

$\psi_j^{Occ(i)}$ **Quartile**	**Managers**	**White Collars**	**Blue Collars**
1^{st}	273.23	68.69	54.17
2^{nd}	335.26	85.86	60.91
3^{rd}	399.93	92.47	66.48
4^{th}	400.36	113.64	74.79
N workers	8,780	301,379	454,246
N firms	1,609	5,311	4,358

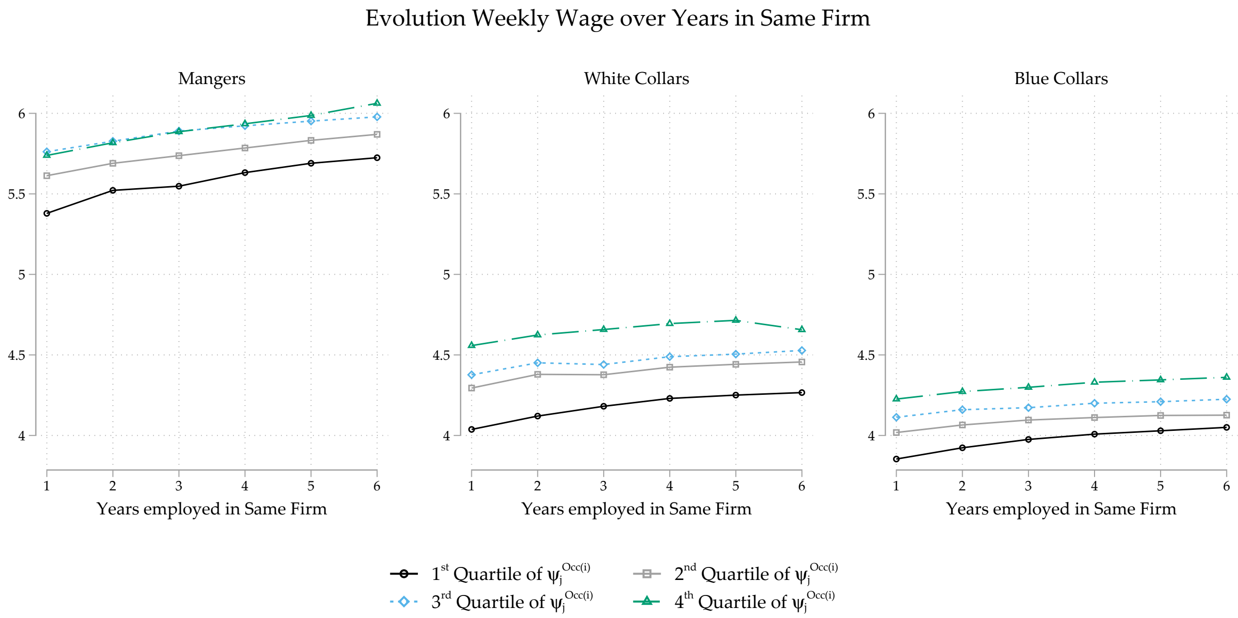
Notes: The table reports average daily wages in 2003 euros for managers, white collars and blue collars by quartiles of the occupation-specific firm fixed effects distribution. The estimated wages are based on job spells of workers working in firms located in Veneto and belonging to the three occupation specific largest connected sets. Among managers, mid-managers (*quadri*) are excluded form the estimation.

Table 2: Average daily wage along the distribution of $\psi_j^{Occ(i)}$.

Table 2 and Figure 1 confirm the existence of "good" and "bad" firms type *within* each occupational class: with respect to workers employed at the top of 25% of ψ_j^{Occ}, if employed in a firm belonging to the bottom 25%, managers earn 32% less, white collars 40% and blue collars 28%.

I then explore whether workers' and employers' characteristics help predict the distribution of $\psi_j^{Occ(i)}$.

[13] I distinguish 5 classes of firms depending on the number of employees: firms with less than 10, between 10 and 20, between 21 and 200, between 201 and 500, more than 500 employees.



Notes. The figure plots for each occupational class the average daily wage of workers employed for subsequent years in firms belonging to different quartiles of the firm fixed effect distribution for the time period 1996-2001. Estimates are based on the occupation-specific largest connected set.

Figure 1: Daily Wages along the occupation-specific firm fixed effects distribution.

$\mathbf{Pr}(i \in F(\psi_j) \geq \mathbf{0.5})$	**Managers**		**White Collars**		**Blue Collars**	
	β	*P-value*	β	*P-value*	β	*P-value*
Female	.017	.0013	-.044	0	-.16	0
Age above 45	.023	0	.056	0	.058	0
Firm with more than 200 employees	.092	0	.042	0	.04	0
Firm in finance and insurance sector	.057	0	.41	0	.026	0
Firm in Service Sector	-.14	0	-.13	0	.093	0
N Workers	24763		301379		454246	
N Firms	1,927		5,311		4,358	
N person-year obs	80,916		988,881		1,518,028	

Notes: The table reports the results for a simple Probit model. The depenendt variable equals one if the worker is employed in a firm at top-half of the $\psi^{Occ(i)}$ distribution. In the model we then control for worker's gender and age (dummy equal to one if worker is older than 45 years old), employers' size (dummy equal to one if fimr has more than 200 employees) and two dummies indicating if the worker is employed in a firm operating in the finance or service sector. Year and province fixed effects are added as controls. The estimation sample comprises all workers and firms belonging to the occupation-specific connected sets and that are located in Veneto.

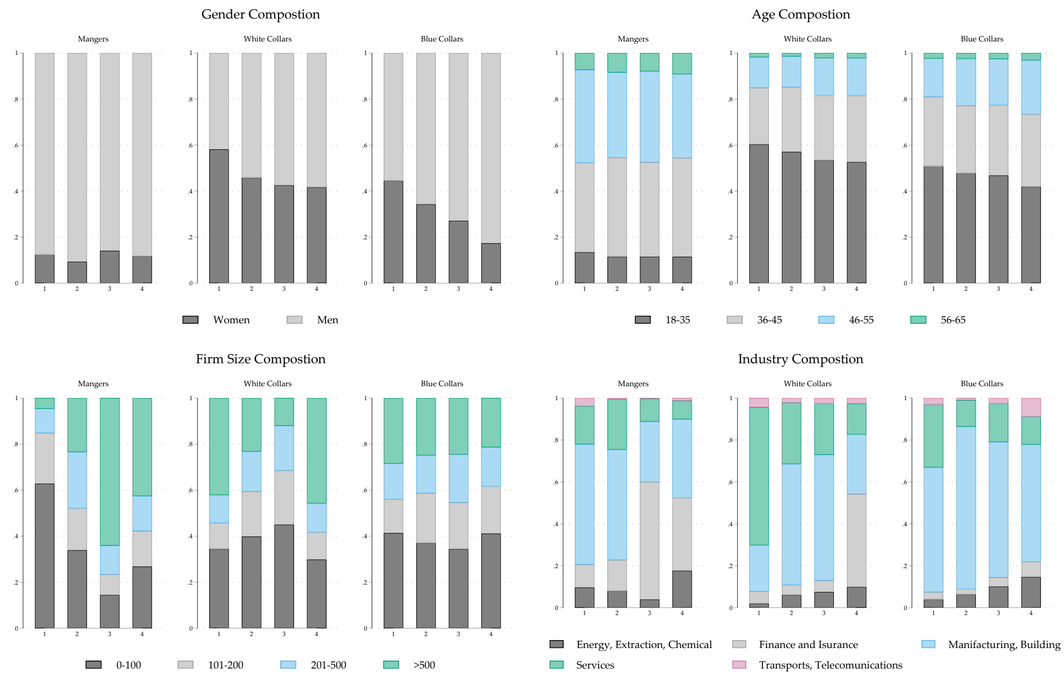
Table 3: Probability of working in a firm belonging to the top-half of ψ_j^{Occ} distribution.

Figure 2 shows for each occupational class, the workers' gender and age composition as well as the employers' size and industrial sector composition along quartiles of $\psi_j^{Occ(i)}$. In the upper-left panel of Figure2 it is immediate to see a clear adverse selection of women along both ψ_j^{WC} and ψ_j^{WC}. These results are in line with gender-biased sorting of workers into firms largely documented by previous literature [Card et al., 2013, Bruns, 2019, Casarico and Lattanzio, 2019, Fanfani, 2022]. Similarly, in the upper-right panel, we can see that the age composition of workers is decreasing along $\psi_j^{Occ(i)}$. In particular, consistently with findings by Kline et al. [2020], workers younger than 35 are more likely to be employed in bad rather than good firms.

In the lower panels of Figure 2, I plot the composition of quartiles of $\psi_j^{Occ(i)}$ by 4 main firm size classes and 5 main industrial sectors.[14] It is possible to see that managers employed in bigger firms enjoy the highest $\psi_j^{Occ(i)}$, while for both white and blue collars, firm size does not seem to play a big role. Similarly, working in the financial (service) sector is related to the highest (lowest) firm wage policies for both managers and white collars.

Eventually, I formally test observable differences between low- and high-type firms with a probit model where the dependent variable takes value 1 if the worker is employed in a firm belonging to the top 50% of the firm-fixed effect distribution. I include a list of dummy variables distinguishing workers

[14] We consider 4 main firm size classes based on the number of employees per year: firms with less than 100 employees; firms with between 101 and 200 employees per year; firms with between 201 and 500 employees per year; and firms with more than 500 employees per year. Next, we consider 5 main industrial sector groups: energy, extraction and chemical industries; manufacturing and building industries; finance and insurance; services; transport and telecommunications.



Notes. The figure plots for each occupational class the average daily wage of workers employed for subsequent years in firms belonging to different quartiles of the firm fixed effect distribution for the time period 1996-2001. Estimates are based on the occupation-specific largest connected set.

Figure 2: Daily Wages along the occupation-specific firm fixed effects distribution.

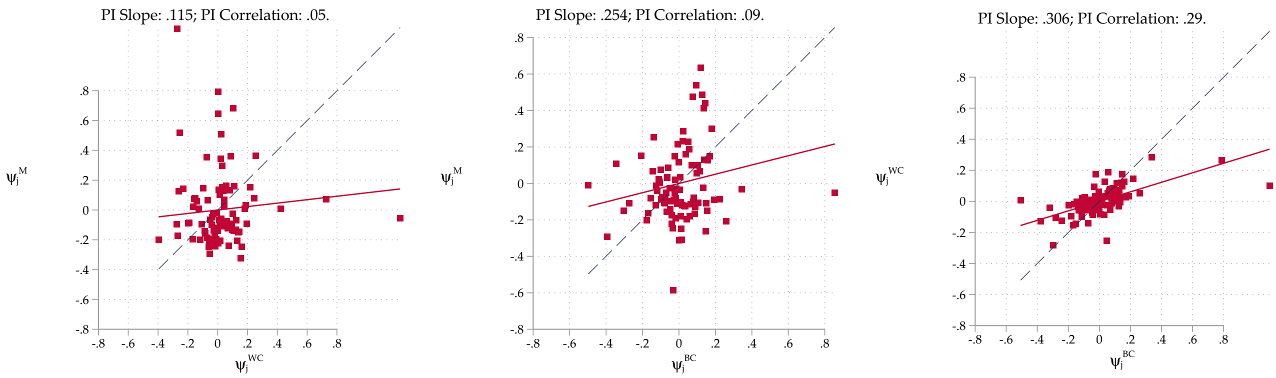
by gender, by age (older than 45 years old), by employer's size (more than 200 employees), by employer's industrial sector (one dummy for finance and one for service sector). I estimate separate models for the three occupation-specific, largest connected sets including year and province fixed effects. Model results are displayed in Table 3. The reported coefficients read as the difference in the probability of being employed in a "good" firm (i.e. a firm that belongs to the top half of the $\psi_j^{Occ(i)}$ distribution) depending on the worker's gender and age and on the employer's size and industrial sector. For example, managers working in the financial (service) sector are 5.7 (14) percentage points more (less) likely to be employed in a high-paying firm, with respect to similar managers employed in other sectors.

Overall, results in Table 3 are in line with the descriptive evidence from Figure 2 and show that a) there is evidence of differences in the worker and firm characteristics along the occupation-specific firm premia distribution and b) these differences are *not* common to each occupational class. In this sense, for instance, working for the financial sector is highly predictable of the firm type for managers and white collars, but not blue collars. While these results provide already some insights about potential heterogeneity in the policy applied within firms to different occupational, they do not answer the question of whether a single firm adopts different pay strategies for its employees based on the occupational class. We explore this specific question in the following paragraphs.

4.1.2 Same Firm different Wage Policies

Once I relax the assumption that $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$, it might be the case that, for example, firm j adopts advantageous pay policies for its managers with respect to the other firm in the market but, at the same time, the firm premium paid to blue collars working in j is relatively un-rewarding. In this case, firm j will be at the top of the $\psi^{Manager}$ distribution and at the bottom of $\psi^{BlueCollar}$ distribution. Thus, firm premia may differ not only by *level*, but also by *rank* between occupational classes. To test this, I estimate correlations in ranks across the different occupation-specific ψ^{Occ} distribution. I restrict the following analysis to the *triple* connected set (TCS), which comprises all those firms connected by worker mobility where I can identify a firm-fixed effect for each occupational class. Within the TCS, I can directly compare the rank and the level of ψ_j^M, ψ_j^{WC} and ψ_j^{BC} because estimated and normalized over the same support of firms.

The red lines in Figure 3 provide the coefficient of the person-year weighted projection of $\psi_j^{Manager}$ onto $\psi_j^{WhiteCollar}$ in the left panel, the projection of $\psi_j^{Manager}$ onto $\psi_j^{BlueCollar}$ in the central panel, and the projection of $\psi_j^{WhiteCollar}$ onto $\psi_j^{BlueCollar}$ in the right panel. The firm premia are estimated here using the triple connected set in order to have the same sub-sample of firms in each $\psi_j^{Occ(i)}$ distribution.[15] Under the assumption $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$ the estimated projection slopes should coincide with the 45 degree line. However, the low estimated correlations indicate that firms occupy substantially different ranks along the firm premia distribution depending on the occupational class.



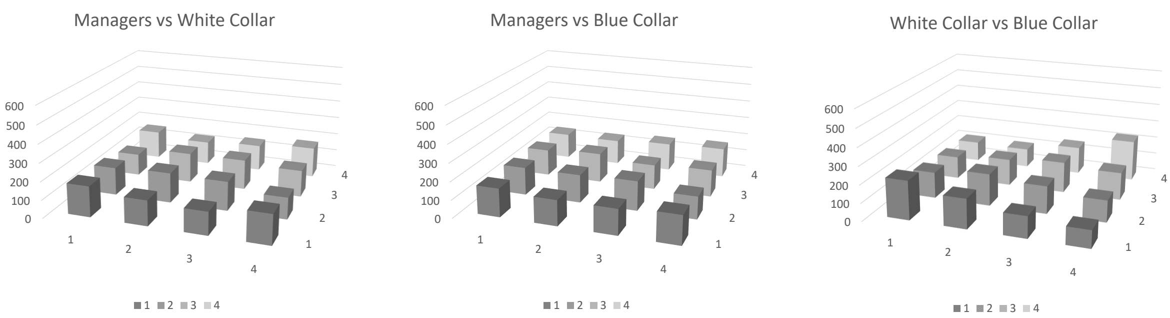
Notes. Estimation on the triple connected set over the period 1996-2001. Each set of firm fixed effect have been demeaned. $PI slope$ in the figure 3 indicates the coefficient of the projection of $\psi_j^{Manager}$ onto $\psi_j^{WhiteCollar}$ in the left panel, the projection of $\psi_j^{Manager}$ onto $\psi_j^{BlueCollar}$ in the central panel and the projection of $\psi_j^{WhiteCollar}$ onto $\psi_j^{BlueCollar}$ in the right panel. $PI correlation$ gives the person-year weighted sample correlation between occupation-specific firm premia.

Figure 3: Do firm premia differ between occupational classes?

As further test, in Figure 4, I take the 2,410 firms in the triple connected set and sort them based on their rank over quartiles of the $\psi^{Manager}$, $\psi^{WhiteCollar}$ and $\psi^{BlueCollar}$ distribution. I then cross-compare the ranks that the same firm has on the manager, white collars, and blue collars firm premia distribution. If firms would apply same pay strategies to all their employees, the bars in Figure 4 should be clustered along the main diagonal. Instead, firms are scattered across all the possible rank interactions.

The analysis above shows that once the assumption $\psi_j^{Manager} = \psi_j^{WhiteCollar} = \psi_j^{BlueCollar}$ is relaxed, substantial heterogeneity emerges. Such variability lies between *and* within firms since, as Figure 3 and 4 show, a single firm adopts diversified compensation strategies for its employees depending

[15] The same test is applied in Kline et al. [2020] for checking whether firms premia differ between younger and older employees.



Notes. Estimation on the triple connected set over the 1996-2001 period. The figure counts firms over 16 cells of occupation-specific firm effects (4 quartiles per occupational group).

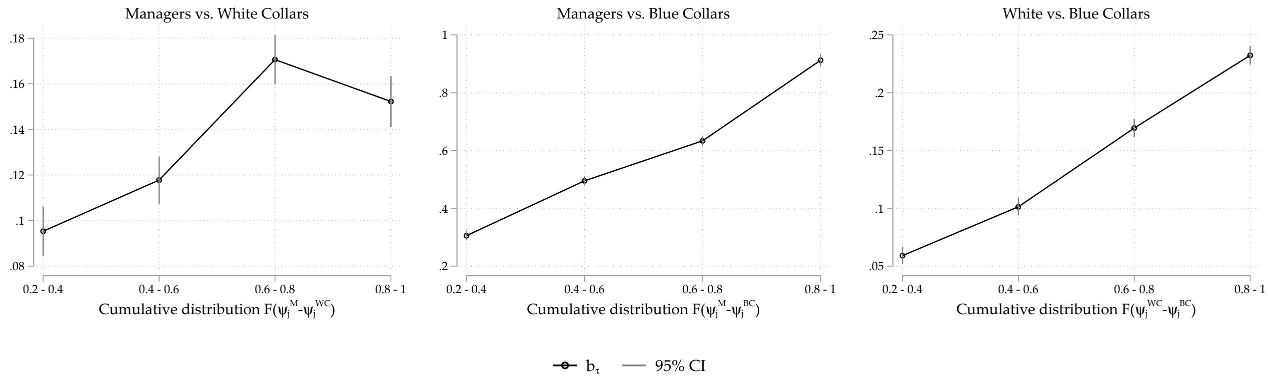
Figure 4: Joint Distribution of the occupation-specific Firms Premia.

on their occupation.

An interesting aspect to investigate is the extent of the within-firm wage differences between occupational classes. As explained in Section 2, equation 2 adapts the model for the estimation of firm-specific gender gaps proposed by Fanfani [2022] to test within-firm differences in occupational returns. Firms in the TCS are sorted according to metric $\mu_j^{X-Y} = \psi_j^X - \psi_j^Y$ defining quintiles of increasingly more favorable firms for the occupational group X with respect to occupational group Y. The coefficient of interest is b_τ and measures the additional wage premia that occupation X gains if employed in firms that have increasingly more favorable wage policies for occupation X with respect to occupation Y, *ceteris paribus*. Figure 5 reports estimates of b_τ for each combination of occupational groups.

Results show that a relevant wage gradient exists between the occupation-specific wage policies applied by firms. In the case of white and blue collars (right-hand panel in Figure 5), b_τ is always positive and increasing along the distribution $F(\mu_j)$. Specifically, white collars earn an additional 6% wage premium on blue collar peers if employed between the first and second quintiles of $F(\mu_)$. This wage premium for white collars increases by 10% if employed in a firm between the second and third quintiles, by 17% between the third and fourth quintiles and by 23% if employed in the 20% most discriminatory firms, *ceteris paribus*. Similar patterns can be observed between managers and white collars (left-hand panel), and between managers and blue collars (middle panel).

Eventually, it is important to understand how $F(\mu_j)$ and $F(\psi_j)$ are related. In particular, I would like to know if the most discriminatory firms in terms of occupation-specific wage policies, are also those

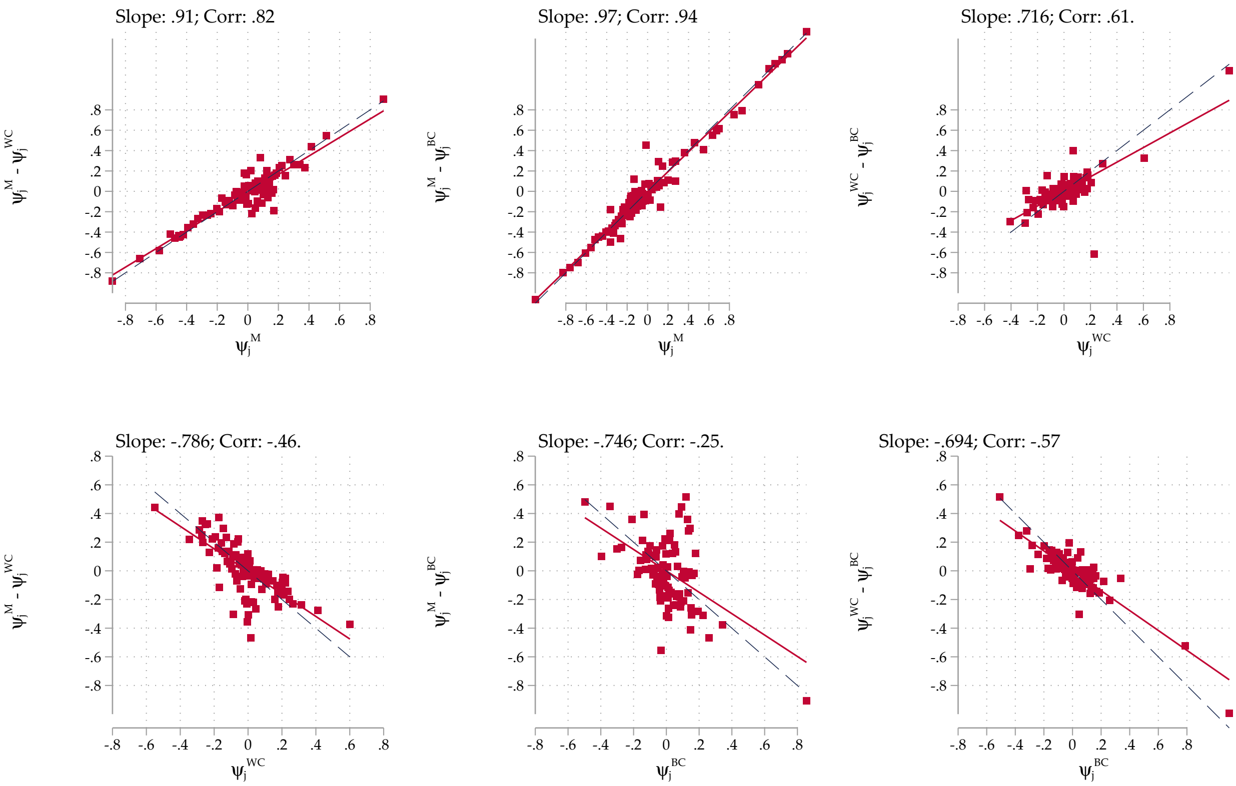


Notes. The figure reports estimation of b_τ according to model 2 for managers over white collars in the panel on the left, for managers over blue collars in the middle panel, and for white over blue collars in the panel on the right. Estimation on the triple connected set over the 1996-2001 period restricted to firms located in Veneto. Results for managers comprise both executive and middle-level managers (*quadri*)

Figure 5: Within-firm wage gradient.

that are the most advantageous for a given occupational class. If this were the case, among white and blue collars, for example, $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$ and $F(\psi_j^{WC})$ would be positively related. Similarly for Figure 3, Figure 6 shows the projection of μ_j onto percentiles of ψ_j for the different combinations of occupation-specific firm fixed effects. In the three upper panels of Figure 6, correlation is confirmed to be strong and positive, suggesting that the "best" firms for each occupational class are also those that are the most discriminatory against the others. For example, in the case of white and blue collars (upper right panel) it is immediate to see that those firms that have a strong discriminatory policy (large $\mu_j = \psi_j^{WC} - \psi_j^{BC}$)) are located at the top of the ψ_j^{WC} distribution. In the three lower panels of Figure 6, instead, I show the correlation between $F(\mu_j)$ and the firm fixed effects for the occupational class that is discriminated against. Correlation is negative and in general lower, meaning that the most discriminatory firms against a given occupational group are also those that apply relatively low pay policies for these classes.

These results corroborate the previous findings: not only do the same firms apply different wage policies to its employees, but the highest-paying firms for a given occupational group are likely to be the most discriminatory for the others employees.



Notes. Estimation on the triple connected set over the period 1996-2001. Each set of firm fixed effect have been demeaned. *Slope* in the Figure 6 indicates the coefficient of the projection of $\mu_j = \psi_j^M - \psi_j^{WC}$ onto ψ_j^M (ψ_j^{WC}) in the upper (lower) left panel, the projection of $\mu_j = \psi_j^M - \psi_j^{BC}$ onto ψ_j^M (ψ_j^{BC}) in the upper (lower) central panel and the projection of $\mu_j = \psi_j^{WC} - \psi_j^{BC}$ onto ψ_j^{WC} (ψ_j^{BC}) in the upper(lower) right panel. *Correlation* gives the person-year weighted sample correlation between μ_j and ψ_j.

Figure 6: Correlation μ_j and ψ_j

4.2 Long-run Analysis: 1980s vs. 1990s

In the following section, I study the evolution of occupation-specific firm premia over time, assessing whether the role of firms in inequality changed between the 1980s (1982-1991) and the 90s (1992-2001) in Veneto region. Concepts and methodologies are the same applied for the 1996 - 2001 analysis explained above. The unique difference is that, because of data limitations, I cannot distinguish mid-managers (*quadri*) from white collars before 1996. In order to have consistent and comparable samples over time, in the following exercises managers are incorporated to white collars. Consequently, for each firm in the data, I distinguish two, rather than three, occupation-specific wage policies, ψ_j^{WC} and ψ_j^{BC}. Therefore, in our working sample, I consider all those firms in VWH that have at least one white collar *and* one blue collar.[16] As before, I focus on unique job spells per year of workers aged 18-64 who are not in their apprenticeship and who are employed for at least four months (16 weeks) in a year. Table 5 in the Appendix summarizes the main descriptive statistics for both the 1980s and 90s working-sub-samples in the occupation-specific largest connected sets and in the *double* connected set.[17]

4.2.1 Did firm policies changed over time?

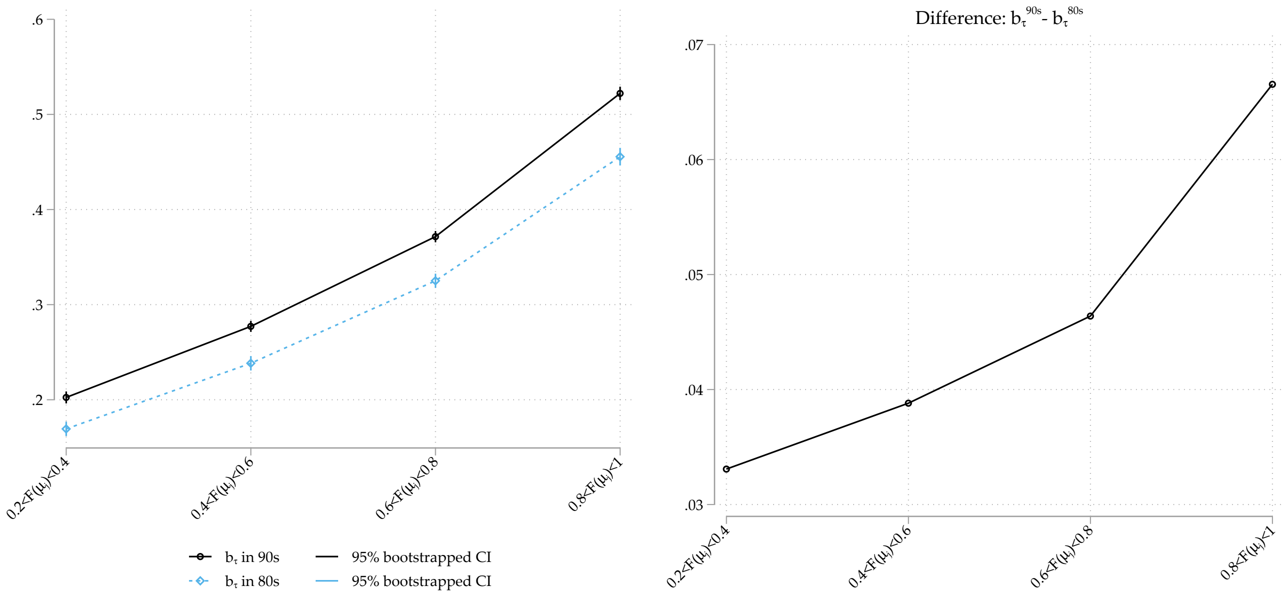
I first estimate, in each period, two separate AKM models on the white and blue collar largest connected set. Table XX in Appendix A summarizes the results. Figure 10 in Appendix A shows the average (log-) daily wage of blue and white collar workers employed for subsequent years in firms belonging to different quartiles of the firm fixed effect distribution. As for the short panel 1996-2001, we notice that firm fixed effects predict well the substantial heterogeneity in the wage *levels* across workers employed in the same occupational group. We then estimate within the DCS, new AKM models to retrieve ψ_j^{WC} and ψ_j^{BC} that are directly comparable within the same time frame. This allows for replicating Figure 3 and Figure 4 for both the 1990s and 80s. The resulting figures are shown in Appendix A and confirm, like the previous section, a weak relationship between $F(\psi_j^{WC})$ and $F(\psi_j^{BC})$. Therefore, even in the long run, firms seem to have applied different wage policies to their employees depending on the occupational classes.

Thus, an interesting aspect to investigate is whether differences *within* firms have expanded, reduced, or remained constant over time. To do so, first I estimate model 2 in both time intervals and then compare the results. Figure 7 shows on the left side b_τ estimated in the 90s in black and the b_τ estimated in the

[16] In the previous section, the data restriction was much tighter since I only considered firms with at least one manager as eligible for the connected set.

[17] As for the triple connected set, the double connected set (DCS) comprise all those firms connected by white *and* blue collars mobility. Thus, within the DCS, it is possible to estimate both ψ_j^{WC} and ψ_j^{BC} for each firm j.

80s in light blue. The right panel of Figure 7 plots the over time difference in the estimated coefficients. Our results show that within-firms pay policies differentials increased in the 90s with respect to the 80s and such increase has been larger the higher $F(\mu_j)$. In other words, between the 80s and 90s the most advantageous firms in the market for white collars become increasingly less attractive for blue collars.



Notes. The left panel of the figure reports estimation of b_τ according to model 2 for white collars over blue collars for the period 1992-2001 (in black) and for the period 1982-1991 (in light blue). Confidence intervals are obtained via bootstrapping (50 replications). The panel on the right reports the over time difference $b_\tau^{90s} - b_\tau^{80s}$. Estimation on the double connected set restricted to firms located in Veneto

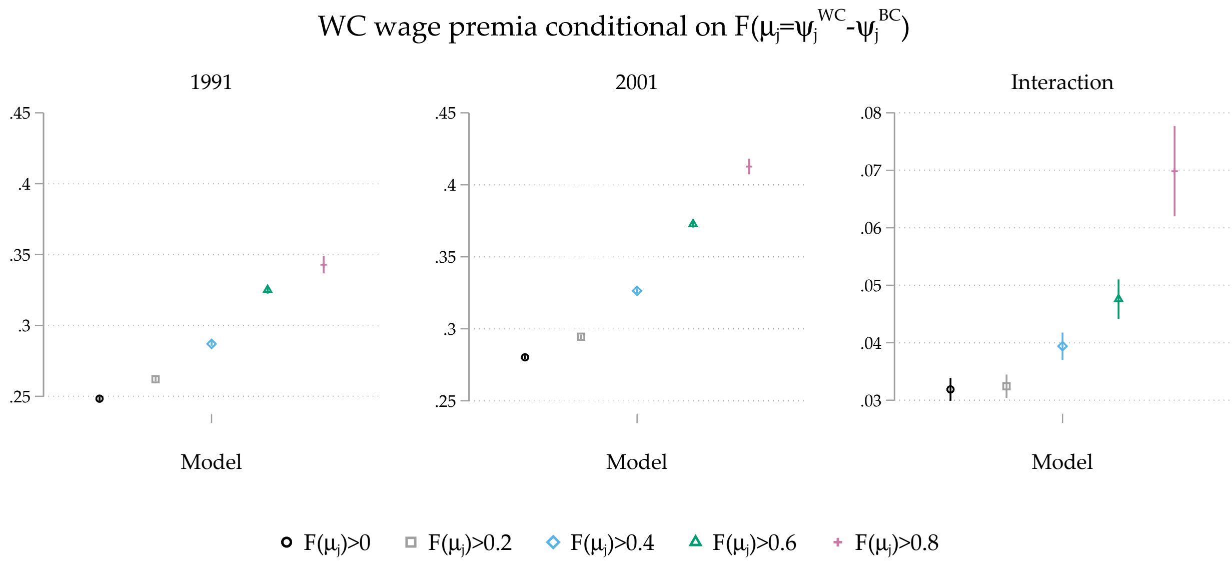
Figure 7: Within-firm wage gradient over time.

I further test these latter findings with a simpler model that, however, allows a more direct comparison between the within-firm pay policies in the 80s and in the 90s. In particular, I first restrict the working sample to the latest wave available in both periods, i.e. 1991 and 2001. Then, I run the following model:

$$ln(w_{it}|i \in F(\mu_j > \tau) = b^{\tau}_{wc}1[g = WC] + \delta^{\tau}_{wc}1[g = WC] * 1[t = 2001] + X_{i,t}\beta^{\tau} + X_{i,t}1[t = 2001]\gamma^{\tau} + \omega_j + \epsilon_{it} \quad (5)$$

where w_{it} is the daily wage of worker i employed at time t in a firm j belonging to the right tail of the distribution $F(\mu_j = \psi_j^{WC} - \psi_j^{BC} > \tau)$, with $\tau = \{0; 0.2; 0.4; 0.6; 0.8\}$. $1[g = WC]$ is a dummy that takes value 1 if the worker is employed as white collar, 0 if employed as a blue collar. Similarly,

$1[t = 2001]$ is a dummy that takes value 1 if the job spell is observed in year 2001, 0 if observed in 1991. Therefore, coefficient $\_wc^{\tau}$ provides the average wage premium that white collar workers earned over blue collar workers in 1991 when employed in a firm belonging to $F(\mu_j = \psi_j^{WC} - \psi_j^{BC} > \tau)$.[18], while the coefficient δ_{wc}^{τ} represent difference between the white collar premia observed in 2001 and 1991. Next, we include in the model a full set of observable individual characteristics, X[19] and a firms fixed effects, ω_j, common to both white and blue collars. Individual level observable characteristics are interacted with the time dummy $1[g = WC]$. Results are shown in Figure 8 and confirm model 2 predictions shown in Figure 7.



Notes. The figure reports the estimates of the main coefficients of interest from model 5. Estimates of b_{wc}^{τ} are reported in the left-hand panel. Estimates of $b_{wc}^{\tau} + \delta_{wc}^{\tau}$ are reported in the middle panel. Estimates of δ_{wc}^{τ} are reported in the right-hand panel. The black marker corresponds to the overall effects, i.e. when $F(\mu_j > 0)$. The gray marker when $F(\mu_j > 0.2)$, the light blue marker when $F(\mu_j > 0.4)$, the green marker when $F(\mu_j > 0.6)$, and the pink marker when $F(\mu_j > 0.8)$. Estimation is restricted to white and blue collars employed in firms located Veneto in 1991 and 2001.

Figure 8: White Collar wage premium conditional on $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$

Overall, in Veneto region, the returns of white collars on blue collar workers increased by 3 percentage points between the 80s and 90s, passing from 0.25 to 0.28. However, this wage premium increase was larger in firms with high discrimination policies $\mu_j = \psi_j^{WC} - \psi_j^{BC}$ and in the top 20% of the discriminatory firms, the white collar premium increased by 7 percentage points.

[18] The equivalent effect for workers employed in 2001 is $b_{wc}^{\tau} + \delta_{wc}^{\tau}$

[19] We control for age, age squared, tenure.

4.2.2 Sorting

A key question to explore is whether the disproportionate increase in white collars returns along the distribution $F(\mu_j)$ is determined by increased sorting of workers into firms, or by increased discrimination of firms with respect to their employees *independently* of changes in the workforce composition. In particular, sorting accounts for the degree of selection of high-type workers in high-type firms and it is usually measured by the covariance between firm and worker effects, $Cov(\psi_j^{Occ}, \theta_i)$, estimated from the occupation-specific largest connected sets.[20] More recently, several papers discuss a series of limitations behind $Cov(\psi_j^{Occ}, \theta_i)$. Kline et al. [2020] show that, in a traditional AKM estimation $Cov(\psi_j^{Occ}, \theta_i)$ is typically downward-biased and this bias is negatively related with the number of movers within the connected set. Thus, the authors propose a bias-correction methodology that relies on the so called "leave-one-out" estimator. Section C in the Appendix is dedicated to present the different methodologies and compare the results. Alternatively, Lopes de Melo [2018] proposed to proxy sorting using the correlation between the worker's fixed effect, θ_i, and the average fixed effect of coworkers, $\tilde{\theta^j}$.[21] Song et al. [2019] propose a measure of segregation, defined as the propensity of low- and high-type workers to be increasingly likely to be employed in different firms. Formally, the Segregation Index is calculated as the ratio between the variance of the average worker effect in each firm, $Var(\overline{\theta^j}$, and the variance of worker fixed effects, $Var(\theta_i)$. The higher the index, the more firms are differentiated by worker's ability.

Table 4 shows alternative measures for the sorting and segregation of workers into firms in the 1982-1991 and 1992-2001 periods for both white and blue collars. In the upper panel, the table reports measures for $Cov(\psi_j^{Occ}, \theta_i)$, $Corr(\theta_i, \widetilde{\theta^j})$, and the segregation index estimated on the occupation- and period-specific largest connected set. As mentioned in Section 2 and further discussed in Section C of the Appendix, $Cov(\psi_j^{Occ}, \theta_i)$ is typically downward biased when ψ and θ are calculated via the traditional AKM estimator. I, therefore, apply the bias correction proposed by Kline et al. [2020] (KSS) and report the results in the lower panel of the table. Note that the samples used for the estimation of the parameters in the upper and lower table are different. This due to the fact that KSS bias-correction requires at least *two* movers per firms within the connected set for the identification of the relevant parameters. Section C provides a detailed discussion of the methodology.

[20]Lopes de Melo [2018] provides a good overview of previous studies applying AKM models for estimation of sorting effects.

[21]One limitation of the measure is that it does not distinguish the sign of sorting, just its intensity [Lopes de Melo, 2018]. I claim that this does not represent a limitation of the intended analysis, since the aim of the exercise is exactly to test whether the *intensity* of sorting changed between the 80s and 90s in Veneto. Bartolucci et al. [2018] develops an alternative sorting measure index based on firm profits rather than firm AKM fixed effects and provide tests for the sign of sorting. In their paper Bartolucci et al. [2018], using the same dataset as this study, show that both their index and correlation, proposed by Lopes de Melo [2018], are much better proxies for the degree of assortment between workers and firm types in labor markets than the covariance index.

Tradional AKM: Largest Connected Sets	**White Collars**			**Blue Collars**		
	1992-2001	**1982-1991**	Δ	**1992-2001**	**1982-1991**	Δ
$Var(w_{it})$	0.279	0.245	0.034	0.122	0.106	0.016
$Cov(\psi_j^{Occ}, \theta_i)$	-0.009	-0.018	0.009	0.005	-0.012	0.017
$Corr(\theta_i, \widetilde{\theta^j})$	0.441	0.462	-0.020	0.495	0.493	0.002
$Var(\overline{\theta^j})/Var(\theta)$	0.325	0.341	-0.016	0.337	0.330	0.007
N of Firms	58,836	50,206		74,428	62,830	
N Movers	210,984	149,892		493,211	340,989	
N of Person Year Observations	3,411,169	2,937,505		6,837,013	6,263,659	

KSS Bias-Correction: Leave-one-out Set	**White Collars**			**Blue Collars**		
	1992-2001	**1982-1991**	Δ	**1992-2001**	**1982-1991**	Δ
$Var(w_{it})$	0.274	0.243	0.032	0.118	0.102	0.017
AKM Estimates (biased)						
$Cov(\psi_j^{Occ}, \theta_i)$	-0.002	-0.001	-0.001	-0.003	-0.009	0.006
KSS Bias-corrected Estimates (unbiased)						
$Cov(\psi_j^{Occ}, \theta_i)$	0.008	0.009	-0.001	0.001	-0.003	0.004
N of Firms	31,419	26,314		58,284	48,381	
N Movers	185,385	127,458		477,115	326,612	
N of Person Year Observations	2,976,557	2,580,635		6,407,268	5,875,702	

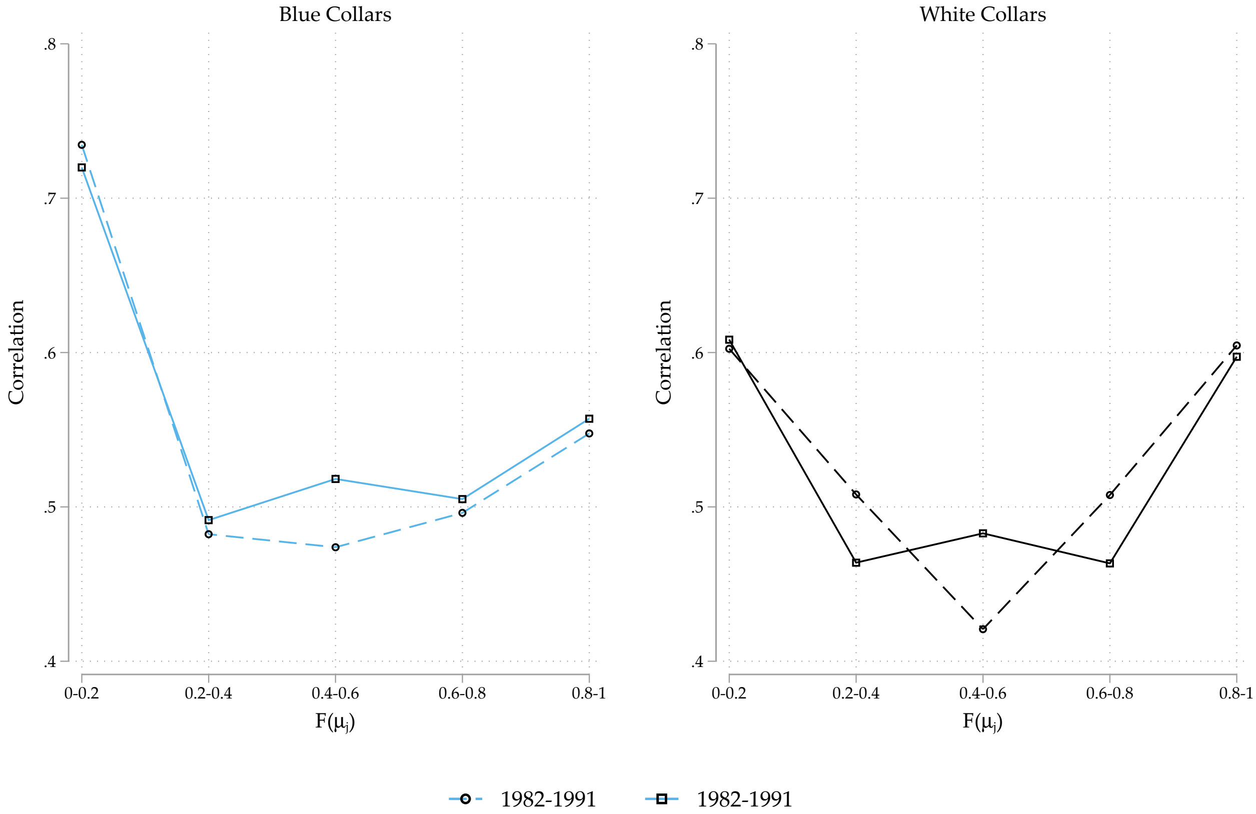
Notes: This table shows different measures of sorting over the 2001-1992 and the 1991-1982 period. The Table is divided in two main panels. The upper panel provides results on the occupation-specific largest connected sets as described in the main text. I report $Corr(\theta_i.\overline{\theta^j})$ and $Var(\overline{\theta^j})/Var(\theta)$. The former represents a measure of sorting as suggested by Lopes de Melo [2018]. the latter is the segregation index adopetd in Song et al. [2019].The lower panel provides results on the Leave-one-out set and compares the biased estimates from traditional AKM with the biased-corrected estimates of $Cov(\psi_j^{Occ}, \theta_i)$ and $Corr(\psi_j^{Occ}, \theta_i)$ according to Kline et al. [2020]

Table 4: Sorting

In the upper panel, all the indicators show that sorting is slightly decreased within white collars and increased within blue collars. Within the leave-one-out sample (lower panel), the KSS estimates confirm these findings, despite the presence of downward biases in the estimation of $Cov(\psi_j^{Occ}, \theta_i)$ via AKM in both periods and for both blue and white collar workers.

Increased sorting within blue collars might help explain the disproportionate increase in the white collar returns along the $F(\mu_j)$ distribution over time. As shown in Figure 13, $F(\mu_j)$ and $F(\psi_j^{BC})$ are negatively related, meaning that the most attractive firms for white collars are typically among the least attractive for blue collars. Increasing sorting among blue collars, might, therefore, reflect a redistribution of high-type blue collar workforce away from high-$F(\mu_j)$ firms toward high-type blue collar firms explaining wage gains for white collars employed in these latter firms that are larger in the 90s with respect to the 80s. To further examine this hypothesis, I next estimate $Corr(\theta; \tilde{\theta^j})$ along the distribution $F(\mu_j)$ and compare the estimates across time periods. This measure has the great advantage of being unbiased and it can be easily estimated at different quantiles of $F(\mu_j)$, providing a *local* proxy for sorting.

Figure 9 shows the $Corr(\theta;\tilde{\theta^j})$ for white and blue collars, estimated within quintiles $F(\mu_j)$, over the 1982-1991 (dash line) and 1992-2001 (solid line) periods. Substantial heterogeneity in sorting intensity emerges from the figure. Interestingly, for both white and blue collars, the major changes in sorting intensity happened at the middle of $F(\mu_j)$, while sorting is found to be unchanged among the most discriminatory firms.



Notes. The figure report the estimates $Corr(\theta;\tilde{\theta^j})$ along the distribution $F(\mu_j)$ over the 1982-1991 (dash line) and 1992-2001 (solid line) periods within each quintile of $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$ for blue (on the left) and white (on the right) collars. Estimation is restricted to white and blue collars employed in firms located Veneto belonging to the double connected set in 1991 and 2001. Managers are included in the estimation of the AKMs and excluded from $Corr(\theta;\tilde{\theta^j})$.

Figure 9: $Corr(\theta;\tilde{\theta^j})$ over $F(\mu_j = \psi_j^{WC} - \psi_j^{BC})$

Overall, These findings provide suggestive evidence that the increasing wage disparities between high- and low-paying firms seem to be determined by an increased segmentation in the remuneration strategies applied by high- and low-paying firms rather than increasing sorting patterns of high- (low-) type workers into high- (low-) type firms. I interpret these findings as a signal of increased wage setting decision power by firms.

5 Conclusions

In this paper, I propose a new perspective on workplace heterogeneity, departing from the implicit assumption in traditional AKM models that, within a single firm, the same wage policy applies to all employees. In particular, I allow employers to set differential firm premia for different occupational classes, i.e. managers, white collars, and blue collars. The main aim of the analysis is to understand whether good firms are actually good for all their employees.

Therefore, I estimate separate AKM models for managers, white collars, and blue collars using administrative data covering the full population of private-sector employees in the Veneto region in Italy. I show that (a) the same firm applies different wage policies to its employees depending on the occupational class. This means that firm j can be highly rewarding for occupational class x and, at the same time, relatively under-rewarding for occupational class y with respect to the other firms in the market. Overall, I find no correlation between the manager, white collars, and blue collars with respect to firm policy distribution, thus providing evidence that the high-type firms are not "equally good" for all their employees.

These findings suggest that while, on average, there exists a clear hierarchy in the returns of the different occupational classes, firms retain a high degree of flexibility in the way in which they remunerate their employees. In particular, the within-firm comparison of occupation-specific firm fixed effects provides direct evidence of the degree of discrimination that firm apply when setting their own occupation-specific polices. Next, I quantify the gradient of occupation-specific remuneration schemes adopted by firms via regression-based models. Ranking employers by the occupation-specific firm fixed effects reveals substantial heterogeneity in the occupational returns that different occupations get if employed in different firm. Most notably, I find that the highest-paying firms for a given occupational group are likely to be among the most discriminatory for the other employees.

Subsequently, I estimate the evolution of such within-firm wage differentials differences over time and find that firm policy discrimination between occupational classes increased in Veneto region between the 1980s and the 1990s. While the white collars increased their returns over blue collars in general, this wage premium increase was larger in firms with high discrimination policies. In order to explain this result, I explored changes in sorting patterns of high-type workers into high-type (occupation-specific) firms. If high discriminatory firms become more efficient in their recruitment process, this might help explain the increase in the occupational gap. However, while I find substantial heterogeneity in sorting intensity between firms with different degrees of pay policy discrimination, the most discriminatory firms in the market did not experienced relevant changes in their workforce composition. Therefore, changes over time in sorting intensity do not seems to explain the increased discrimination.

I interpret these findings as a signal of increased wage setting decision power by firms. Specifically, my findings show that the choice of the employer is a key determinant for worker wage levels, with the consequences of such choices becoming more severe over time.

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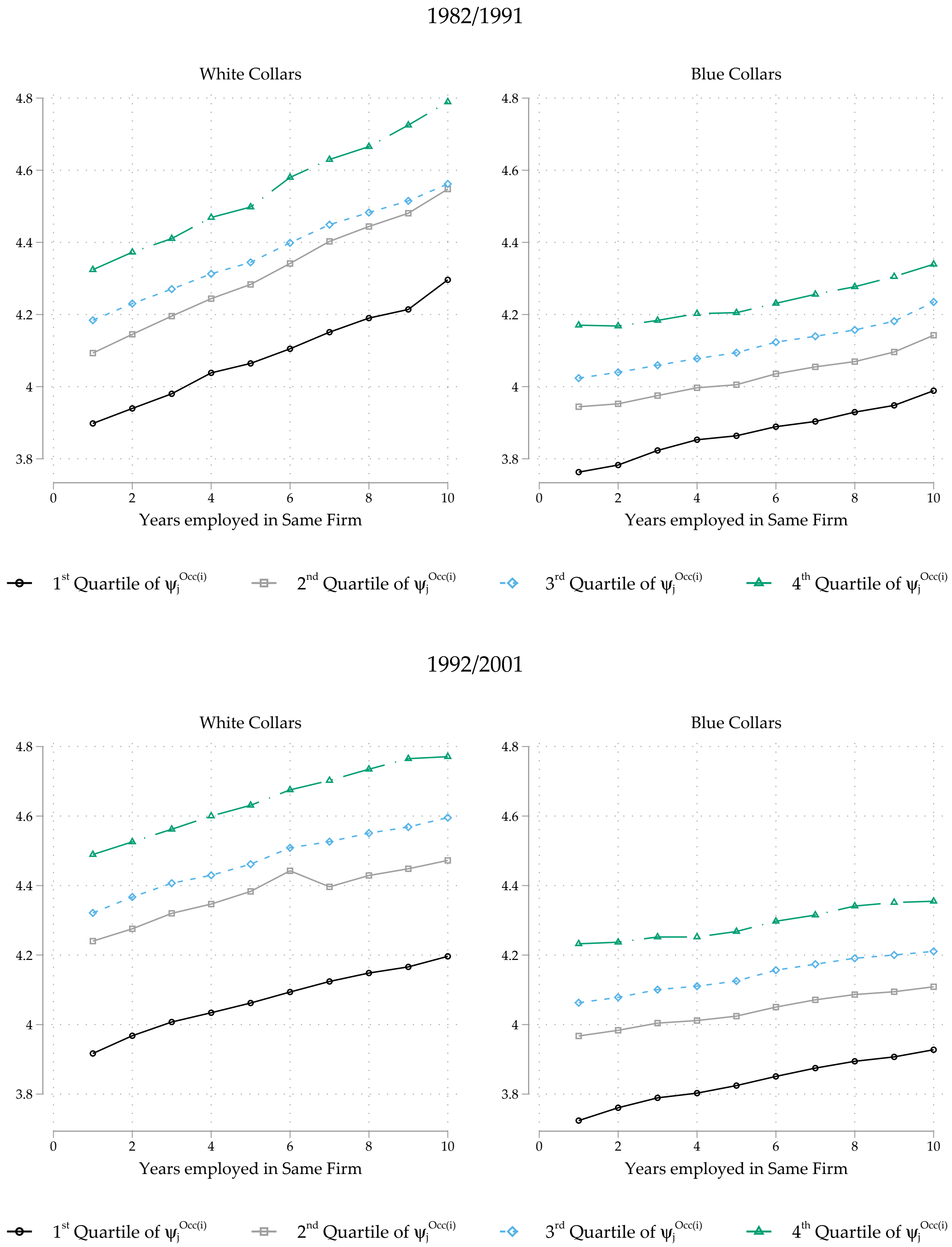
Appendix

Appendix A Supplementary Figures and Tables

	1982-1991				1992-2001			
	Largest Connected Sets		**Double Connected Set**		**Largest Connected Sets**		**Double Connected Set**	
	White Collars	*Blue Collars*	*White Collars*	*Blue Collars*	*White Collars*	*Blue Collars*	*White Collars*	*Blue Collars*
Share of women	.41	.29	.4	.29	.45	.31	.45	.3
Average age	35	36	35	36	36	36	36	36
Average daily wage (2003 euros)	86	61	88	61	96	62	96	63
Avarege Experenice (months)	93	99	94	100	138	136	139	138
Share of workers employed in firms with								
Employees <100	.48	.58	.097	.08	.53	.64	.11	.1
Employees 101-200	.099	.11	.1	.12	.1	.1	.12	.14
Employees 201-500	.11	.13	.36	.45	.1	.11	.4	.47
Employees >500	.31	.18	.12	.14	.27	.15	.11	.12
Share of workers employed as								
Manager	.03	.	.032	.	.029	.	.029	.
White Collars	.97	.	.968	.	.971	.	.971	.
Blue Collars	.	1	0	1	0	1	0	1
Primary Sector	.0048	.0078	.0045	.0063	.0042	.0091	.0042	.0073
Secondary	.4	.68	.44	.68	.45	.66	.47	.66
Secondary	.59	.31	.55	.31	.55	.33	.52	.33
N obs	2.937.505	6.263.659	2.591.507	5.462.147	3.411.169	6.837.013	3.106.097	5.926.512
N workers	599.086	1.211.324	533.319	1.075.856	696.744	1.364.734	641.829	1.226.454
N Firms	50.206	62.830	42.017	42.017	58.836	74.428	51.766	51.766
N obs: % of Overall Sample	.98	.99	.86	.86	.99	.99	.91	.86
N workers: % of Overall Sample	.94	.98	.84	.87	.96	.98	.88	.88
N firms: % of Overall Sample	.65	.82	.55	.55	.69	.87	.6	.6

Notes: Tenure is censored at 1975. Average firms' size is non-weighted and measured by the average of the number of employees working for the company in each year.

Table 5: Descriptive Statics



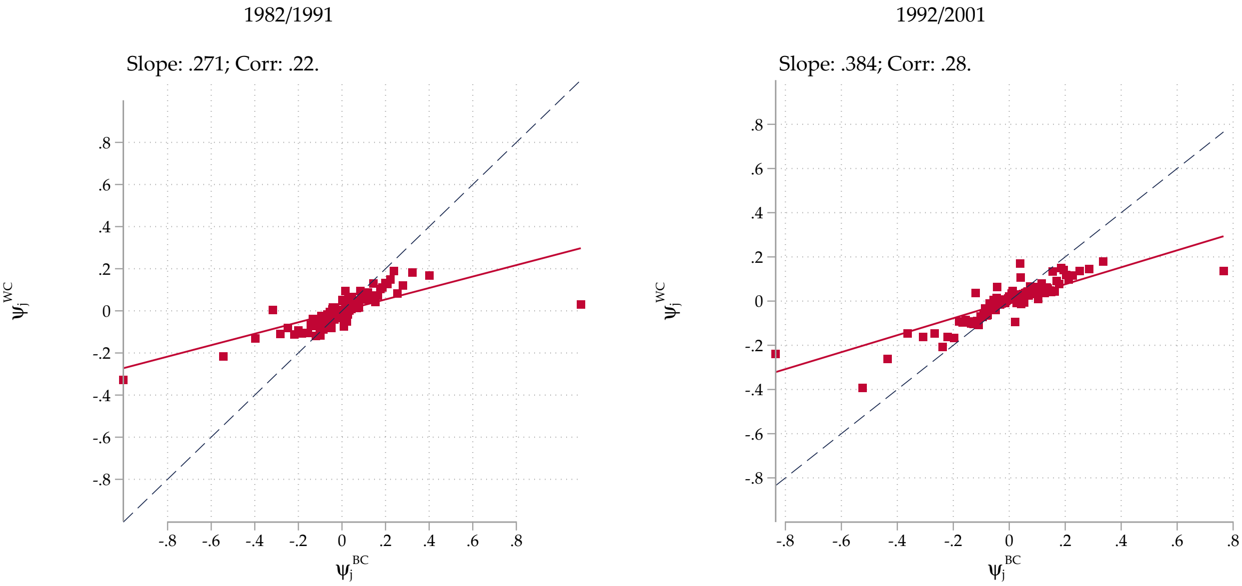
Notes. Estimation on the occupation-specific largest connected set over the 1982-1992 and 1992-2001 periods.

Figure 10: Average log-daily wage along $F(\psi)$.

Quartiles of ψ_j^{Occ}	**1982-1991** *White Collars*	*Blue Collars*	**1992-2001** *White Collars*	*Blue Collars*
1^{st}	61.32	49.38	63.19	48.33
2^{nd}	79.14	56.79	88.17	58.02
3^{rd}	85.36	62.01	98.56	64.11
4^{th}	103.72	72.35	119.36	76.03
N workers	599,086	1,211,324	696,744	1,364,734
N firms	50,206	62,830	58,836	74,428

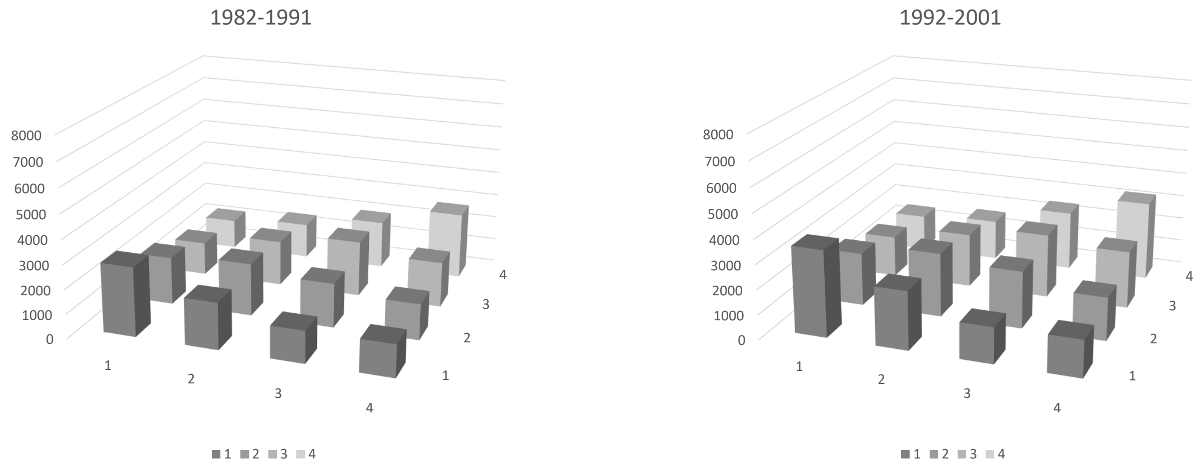
Notes: The table reports average daily wages in 2003 euros for managers, white collars and blue collars by quartiles of the occupation-specific firm fixed effects distribution. The estimated wages are based on job spells of workers working in firms located in Veneto and belonging to the three occupation specific largest connected sets. For managers, mid-managers (*quadri*) are excluded form the estimation.

Table 6: Average daily wage along the distribution of $\psi_j^{Occ(i)}$.



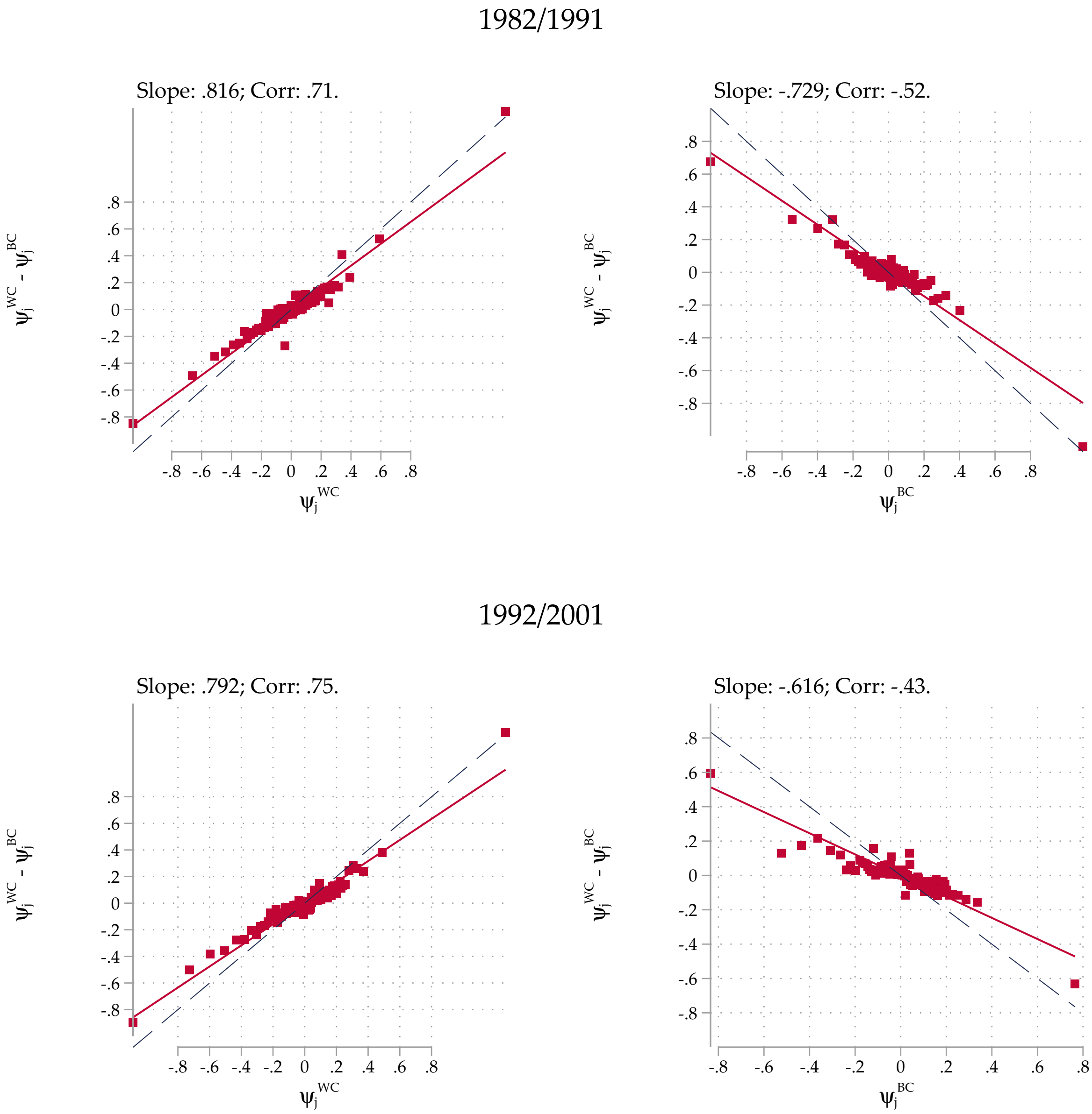
Notes. Estimation on the triple connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. Each set of firm fixed effect have been demeaned. $PIslope$ in the Figure 3 indicates the coefficient of the projection of $\psi_j^{Manager}$ onto $\psi_j^{WhiteCollar}$ in the left panel, the projection of $\psi_j^{Manager}$ onto $\psi_j^{BlueCollar}$ in the central panel, and the projection of $\psi_j^{WhiteCollar}$ onto $\psi_j^{BlueCollar}$ in the right panel. $PIcorrelation$ gives the person-year weighted sample correlation between occupation-specific firm premia.

Figure 11: Do firm premia differ between occupational classes?



Notes. Estimation on the triple connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. The figure counts firms over 16 cells of occupation-specific firm effects (4 quartiles per occupational group).

Figure 12: Joint Distribution of the occupation-specific Firms Premia.



Notes. Estimation on the triple connected set over the 1982-1991 and 1992-2001 periods considering only firms located in Veneto. Each set of firm fixed effect have been demeaned. *Slope* in the Figure 6 indicates the coefficient of the projection of $\mu_j = \psi_j^M - \psi_j^{WC}$ onto ψ_j^M (ψ_j^{WC}) in the upper (lower) left panel, the projection of $\mu_j = \psi_j^M - \psi_j^{BC}$ onto ψ_j^M (ψ_j^{BC}) in the upper (lower) central panel, and the projection of $\mu_j = \psi_j^{WC} - \psi_j^{BC}$ onto ψ_j^{WC} (ψ_j^{BC}) in the upper(lower) right panel. *Correlation* gives the person-year weighted sample correlation between μ_j and ψ_j.

Figure 13: Correlation μ_j and ψ_j over time.

Appendix B Conditional Random Mobility Assumption

Unbiased AKM estimation rely on *conditional random mobility* assumption. Specifically, given:

$$w_{it} = \theta_i + \psi_j + X_{it}\beta + \epsilon_{it} \tag{6}$$

Then,

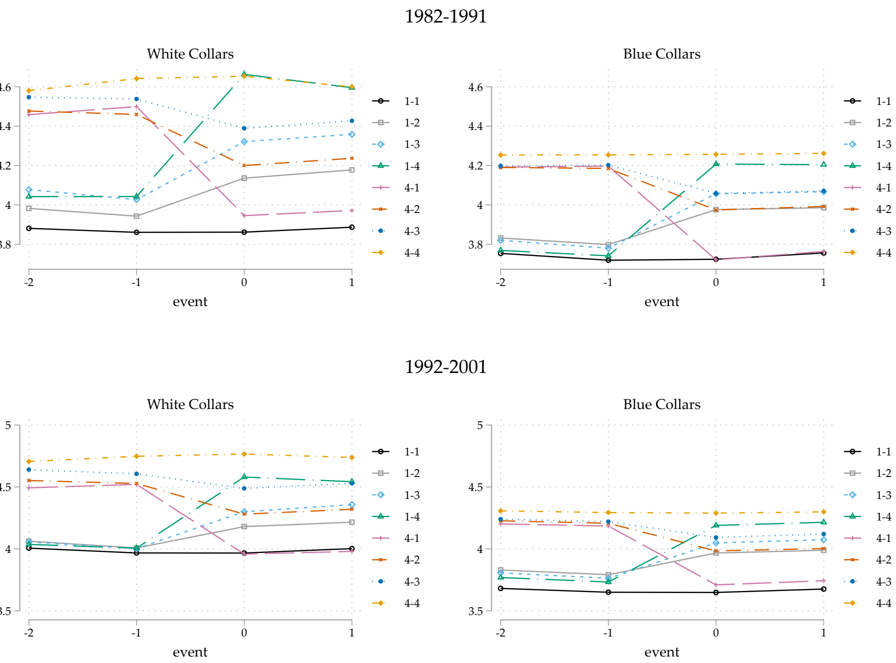
$$E[\epsilon_{it}|X_{it}, \psi_j, \theta_i] = 0 \tag{7}$$

Card et al. [2013] discusses three main channels through which conditional random mobility may be violated and proposes three main empirical tests. I replicate these tests on the largest connected sets for blue and white collars described in Table 5.

First, workers employed in firms experiencing negative shocks could decide to change job and join firms experiencing positive shocks. This would generate correlation between ψ_j and the probability that worker i is employed at firm j at time t . If this is the case, workers would experience a drop in earnings before the move, and a sudden rise in pay after. Figure 14 rules out this possibility.

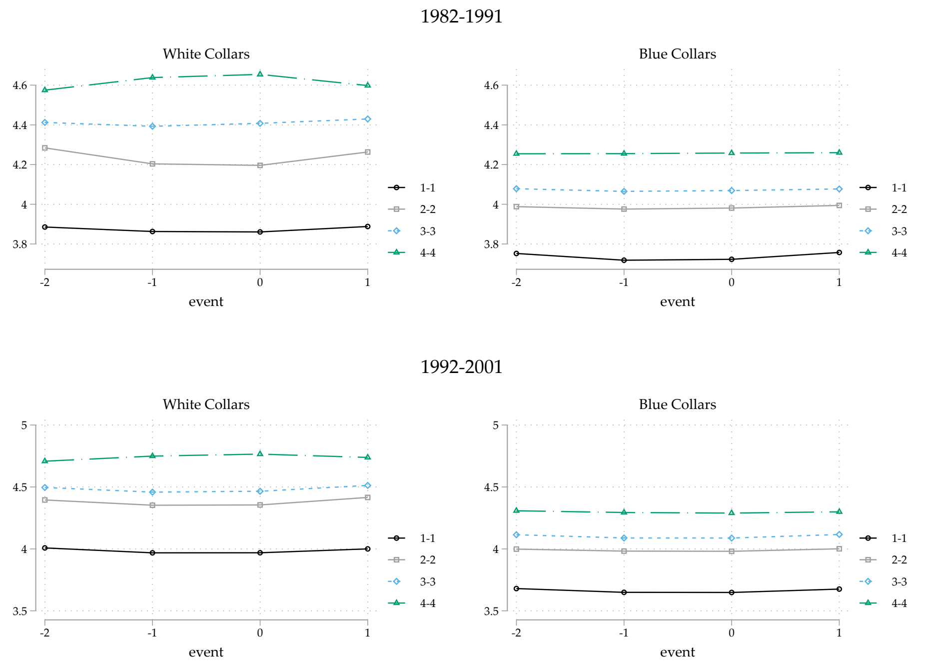
Second, workers could decide to change job would if they think that joining a new firm would deliver a better match between their personal characteristics and the firm characteristics compared to the firm of origin. Figure 15 reports the earnings evolution for the movers within the same quartile in the origin and destination firms. Flat earnings growth suggest that there are no match effects in mobility, thus ensuring that the conditional random mobility assumption is satisfied.

Third, In Figure 16, I plot the average AKM residual in each of the 100 cells defined by the combination of worker and firm fixed effects deciles. If the model is missing some important match component between specific individuals and firms, we would expect to find high mean residuals in those cells that are threatened by miss-specification the most [Casarico and Lattanzio, 2019].



Notes. Estimation on the largest connected set over the 1982-1991 and 1992-2001 periods for both white and blue collars separately.

Figure 14: Average weekly earnings for movers across firm fixed effect quarterlies.



Notes. Estimation on the largest connected set over the 1982-1991 and 1992-2001 periods for both white and blue collars separately.

Figure 15: Average weekly earnings for movers across same firm fixed effect quarterlies.

Notes. Estimation on the largest connected set over the 1982-1991 and 1992-2001 periods for both white and blue collars separately.

Figure 16: Average AKM residuals.

Appendix C Variance decompostion.

C.1 Methodology

In the paper by Abowd et al. [1999], the following variance decomposition is proposed:

$$Var(w_{it})^{Occ} = Var(\theta_i + X_{it}\beta^{Occ(i)})^{Occ} + Var(\psi_j^{Occ(i)})^{Occ} + 2Cov(\theta_i + X_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})^{Occ} + Var(\epsilon_{it})^{Occ} \tag{8}$$

where $\theta_i + X_{it}\beta^{Occ(i)}$ captures the pay component of workers' time-constant and observable time-varying characteristics jointly, simplifying the exposition and discussion of results [Devicienti et al., 2019]. Thus, equation C.1 decomposes total wage variation in the sum of the workers' $(Var(\theta_i + X_{it}\beta^{Occ(i)}))$ and firm premia heterogeneity $(Var(\psi_j^{Occ(i)}))$ mediated by positive or negative sorting of workers types into types of firms adopting specific wage policies $(Cov(\theta_i + X_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)}))$.

Since then, the same exercise has been extensively applied to a variety of countries and applications.[22]. While the main purpose of this paper is to study whether differences in the occupation-specific firm fixed effects, ψ^{Occ}, exists, previous literature greatly focuses on the covariance component $2Cov(\theta_i + X_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$, which is typically interpreted as a measure of sorting of workers into firms. Intuitively, rising assortment of high-type workers into high-type firms should be reflected in increasing covariance between worker and firm fixed effects. However, several papers discuss a series of limitations behind the covariance index and propose new methodologies for the estimation of sorting. First, non-monetary amenities might be related to the job choice of employees, such that equally productive workers may be employed by employers adopting very different wage policies. Second, firm fixed effects are *not* a good proxy for firm productivity [Bartolucci et al., 2018]; rather they should be interpreted as capturing the wage differentials paid by companies as results of frictions [Lopes de Melo, 2018]. Thus, introducing these non-linearities between worker and firm types might undermine the interpretation of $2Cov(\theta_i + X_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$. Lopes de Melo [2018] proposes to use the correlation between co-workers' fixed effects as more precise measures for sorting in an economy, while Bartolucci et al. [2018] develop a novel methodology based on firm profits rather than firm AKM fixed effects. They also show that both their and the correlation index proposed in Lopes de Melo [2018] are much better proxies for the degree of assortment between workers and firm types in labor markets than the covariance index

[22] Lopes de Melo [2018] provides a good overview of previous studies applying the same variance decomposition.

$2Cov(\theta_i + X_{it}\beta^{Occ(i)}, \psi_j^{Occ(i)})$.

Additionally, besides the difficult economic interpretation, [Andrews et al., 2008] formally show that the second moments of the AKM variance decomposition are biased and this bias can be particularly severe in situations where the mobility between firms is limited. In particular, the bias comes from the fact that the vector of estimated fixed effects, $\widehat{\theta_i}$ and ψ_j, suffer from standard least squares estimation error. While under the strict exogeneity assumption that these estimation errors are expected to be equal to 0, such that $E[\widehat{\psi_j} = \psi_j]$ is unbiased, the second moment $\widehat{\psi_j}^2$ ultimately depends on the variance of the error term ϵ_i, t, σ_i. In the traditional AKM model, $Var(\psi_j)$ is calculated "plugging-in" the OLS estimate $\widehat{\psi_j}, sothat:$

$$Var(\widehat{\psi_j}) = Var(\psi_j) + \sum_{i=1}^{N} \mathbf{B}_{ii}\sigma_i^2 (9)$$

where $\sum_{i=1}^{N} B_{ii}\sigma_i^2$ is the so called "plug-in" bias and depends on the number of movers per firm.[23]

Bonhomme et al. [2019] propose a two-step estimation approach that relies on clustering similar firms into groups and then estimating the fixed effects at the cluster level. In their preferred specification, they rely on 10 major clusters. In their framework, thus, Bonhomme et al. [2019] exploit mobility between clusters of firms, and not of single firms, for the identification of the relevant parameters, allowing for a higher degree of connection within the estimation sample. While this approach solves the limited mobility bias at the cost, it means reducing the heterogeneity of fixed effects from the firm level to the cluster level.

Kline et al. [2020] (KSS), instead, proposed an alternative *unbiased* estimator for σ_i^2 that allows for empirically computing a bias correction $\sum_{i=1}^{N} B_{ii}\widehat{\sigma_i}^2$ for equation C.1:

$$\widehat{\sigma_i}^2 = y_i(yi - x_i'\widehat{\rho_{-i}})^2 \tag{10}$$

where $\widehat{\rho_{-i}}$ is the OLS estimates of ψ_j, θ_i, and β in equation 1 when observation i is left out. Therefore, the KSS estimator allows for correcting the bias in the estimation of $Var(\widehat{\psi_j})$, $Var(\widehat{\theta_i})$, and $Cov(\widehat{\psi_j}, \widehat{\theta_i})$ within the so called *leave-one out* connected set, which requires dropping any firm associated with only one mover from the AKM largest connected set. Next, it is important to underline that estimation of $\widehat{\rho_{-i}}$ requires solving a system of NxT equations in $N + J$ unknowns where, N represents the number

[23] See Kline et al. [2020] and Lachowska et al. [2022] for details.

of workers in the sample, T the number of years considered, and J the number of firms within the leave-one-out connected set. This computation is infeasible in large matched employer-employees data and it is based on a variation of the Johnson-Lindestrauss approximation algorithm developed by KSS and available as replication package in Matlab.

C.2 Results

Table 7 reports the estimates of the variance decomposition on the occupation-specific leave-one-out connected set for both time periods. The table confronts the parameters identified with the *biased* AKM plug-in estimators and with the *unbiased* KSS estimator, reported in the upper and lower panels, respectively. Results show that the variance in wages increased for both white and blue collars. The largest source of wage heterogeneity comes from heterogeneity workers fixed effects, while heterogeneity in firm wage policies, $Var(\psi_j)$, accounts for a minor share and it decreases over time. These results are consistent with findings by Devicienti et al. [2019] using the same data source but different working samples. Sorting is instead slightly decreased among white collars and increased among blue collars. KSS estimates confirm upward biases in $Var(\psi_j)$ and downward biases in the estimation of $Cov(\psi_j, \theta_i)$ via traditional AKM models. I report in Table 8 the estimates of the traditional AKM decomposition on the occupation specific largest connected set.

	White Collars							Blue Collars					
	1992-2001		1982-1991		Δ			1992-2001		1982-1991		Δ	
		%		%		%			%		%		%
$Var(w_{i,t}$	0.274	*100*	0.243	*100*	0.032	*0*		0.118	*100*	0.102	*100*	0.017	*0*
PLUG-IN ESTIMATES (BIASED),													
$Var(\psi_j)$	0.036	*13.000*	0.037	*15.221*	-0.001	*-2.221*		0.033	*27.906*	0.034	*33.808*	-0.001	*-5.903*
$Cov(\psi_j, \theta_i)$	-0.002	*-0.741*	-0.001	*-0.298*	-0.001	*-0.442*		-0.003	*-2.117*	-0.009	*-8.404*	0.006	*6.287*
$Var(\theta_i)$	0.178	*64.719*	0.238	*98.191*	-0.061	*-33.472*		0.194	*164.196*	0.287	*282.669*	-0.093	*-118.474*
$Corr(\psi_j, \theta_i)$	-0.026		-0.008		-0.018			-0.031		-0.086		0.055	
BIAS CORRECTED ESTIMATES (KSS)													
$Var(\psi_j)$	0.024	*8.795*	0.025	*10.461*	-0.001	*-1.666*		0.029	*24.388*	0.028	*27.831*	0.001	*-3.444*
$Cov(\psi_j, \theta_i)$	0.008	*2.864*	0.009	*3.818*	-0.001	*-0.954*		0.001	*0.719*	-0.003	*-3.162*	0.004	*3.881*
$Var(\theta_i)$	0.156	*56.828*	0.216	*88.978*	-0.060	*-32.149*		0.180	*152.050*	0.271	*266.332*	-0.091	*-114.283*
$Corr(\psi_j, \theta_i)$	0.128		0.125		0.003			0.012		-0.037		0.049	
# of Movers	185.385		127.458					477.115		326.612			
# of Firms	31.419		*26.314*					58.284		*48.381*			
# of Person Year Observations	2.976.557		*2.580.635*					6.407.268					
	5.875.702												

Notes: This table shows results from the variance decomposition specified in equation C.1 using KSS-bias correction. The estimation sample is the leave-one-out connected set for white and blue collars in the 90s (1992-2001) and 80s (1982-1991). The table is divided in two main panels, the one on the left reporting results for white collars and the one on the right for blue collars. In each panel, the first and thirds columns report variance decomposition estimates for the 1992-2001 and 1982-1991 period respectively. The second and fourth columns display the variance decomposition components as share of total variance. The fifth and sixth column report over time differences.

Table 7: Variance Decomposition - KSS

	White Collars							Blue Collars					
	1992-2001		1982-1991		Δ			1992-2001		1982-1991		Δ	
		%		%		%			%		%		%
Variance Decomposition													
$Var(w_{i,t})$	0.279	*100.000*	0.245	*100.000*	0.034	*0.000*		0.122	*100.000*	0.106	*100.000*	0.016	*0.000*
$Var(\theta_i + X_i, t\beta)$	0.205	*73.368*	0.177	*72.289*	0.028	*1.079*		0.057	*46.261*	0.047	*44.692*	0.009	*1.569*
$Var(\psi_j)$	0.045	*16.237*	0.046	*18.934*	-0.001	*-2.697*		0.036	*29.053*	0.037	*34.744*	-0.001	*-5.690*
$Var(\epsilon_{i,t})$	0.026	*9.345*	0.030	*12.258*	-0.004	*-2.913*		0.022	*17.893*	0.029	*26.942*	-0.007	*-9.049*
$Cov(\psi_j^{Occ}, \theta_i + X_{it}\beta)$	0.003	*1.051*	-0.009	*-3.480*	0.011	*4.531*		0.008	*6.792*	-0.007	*-6.378*	0.015	*13.170*
Alternative Sorting and Segregation Measures													
$Corr(\theta_i, \overline{\theta^j})$	0.441		0.462		-0.020			0.495	*0.493*	0.493		0.002	
$Var(\overline{\theta^j})$	0.047		0.062		-0.015			0.018	*0.023*	0.023		-0.005	
Segregation Index	0.325		0.341		-0.016			0.337	*0.330*	0.330		0.007	
$Corr(\psi_j, \psi_j^{Prev})$ *	0.384		0.390		-0.006			0.386	*0.308*	0.308		0.078	
N firms	58,836		50,206					74,428		628,30			
N workers	696,744		599,086					1,364,734		1,211,324			
N movers	210,984		149,892					493,211		340,989			

Notes: This table shows results from the variance decomposition specified in equation C.1 using traditional AKM models. The estimation sample is the largest connected set for white and blue collars in the 90s (1992-2001) and 80s (1982-1991). The table is divided in two main panels, the one on the left reporting results for white collars and the one on the right for blue collars. In each panel, the first and thirds columns report variance decomposition estimates for the 1992-2001 and 1982-1991 period respectively. The second and fourth columns display the variance decomposition components as share of total variance. The fifth and sixth column report over time differences.

Table 8: Variance Decomposition - Traditional AKM