The Value of Outside Options: Measurement, Impact and Inequality

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Do wages in other firms shape employment outcomes? This paper adopts a peer effects framework combined with machine learning methods to identify workers' relevant labor markets and estimate the influence of their quality and structure on wages. High-wage workers tend to work in better-paying markets, but their outside options are worse relative to their current firm. Furthermore, I find that a 10% increase in the quality of other firms in the market is associated with an increase in real wages by 3%, on average. However, controlling for common market shocks flips this sign, showing evidence of a strong wage markdown consistent with backloaded pay structures. This effect is stronger for new hires and less skilled workers. Finally, I show that the structure and quality of labor markets matter for inequality: about 15% of the wage variance in Portugal can be explained by differences in market-specific pay premia.

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1. Introduction

Do wages in other firms matter for my own wage? Understanding the extent to which individual wages depend on the pay practices of competing firms is a crucial step toward understanding how wages are set and why persistent wage inequality arises. If firms adjust their wage offers in response to those of others, labor markets become not just a collection of bilateral employer–employee relationships, but a network in which firms' strategies are interdependent. This enhances the role of labor market power, as firms can leverage this to mark down wages relative to productivity. Exploring this interdependence can shed light on the sources of wage dispersion, the mechanisms that sustain inequality, and the role of competition in shaping pay.

The idea that outside options influence wage setting has a long theoretical tradition (Farber 1986; Pissarides 2000). Yet, translating these insights into empirical evidence has proven difficult. A central challenge lies in identifying a worker's relevant labor market (i.e., who their true competitors and alternatives are) and in measuring the degree of wage interdependence across firms. Without accounting for the networked structure of the labor market, and the possibility that firms react to one another's wage policies, empirical analyses risk drawing biased conclusions about how wages are formed and how inequality emerges.

In this paper, I estimate the impact of other firms' pay policies on a worker's wage, conditional on observed and unobserved characteristics, using matched employer-employee data covering the universe of Portuguese private firms from 2010 to 2021. Drawing from the peer effects literature, I construct a non-linear least squares estimator that enables the estimation of worker, firm and market unobserved heterogeneity parameters while simultaneously recovering how the quality of other firms in the labor market affects wages. In a naive model without market-year fixed effects, I find that a 10% increase in the average quality of outside firms (as given by their firm fixed effects) is associated with a 2.8% increase in real hourly wages. However, when controlling for common shocks to the market that affect outside options simultaneously for all workers, the sign flips, with this elasticity turning to -0.1. These findings show that the effect of labor market quality can be split into two main determinants: the outside options channel, and the quit/renegotiation channel.

The starting point for the analysis is a search model with bargaining and renegotiation as in Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006). These models were innovative due to their introduction of Bertrand-style competition for workers between firms on top of Nash bargaining. As in typical models of the labor market (Pissarides 2000), workers get a share of their outside option through Nash bargaining. With on-the-job search, employees can find offers in the labor market that improve their well-being. By threatening to leave their post, workers can try to renegotiate their current contract to obtain better conditions, provided that their employers are willing to renegotiate. This threat generates a competitive game between the current firm and the potential new employer that may end in two possibilities: the worker gets a better contract from their current employer, or they separate and she joins a new firm. In both situations, she is guaranteed a better future payout. Interestingly, for a sufficiently large bargaining power of the firm, this structure implies that firms may initially pay a lower wage than the match productivity to the worker as a sort of insurance mechanism against future wage rises. Because the firm anticipates that it will have to compete for the worker in the future, it initially provides a lower wage with a positively steeped future schedule. This markdown depends on the probability that the worker will get a better offer, which, in itself, is a function of the quality of other firms in the market. This is captured in the estimation of the main model in this paper.

To start the analysis, I classify jobs into labor markets. Using the approach of Nimczik (2020), I borrow from the network studies literature – more specifically the work on community detection – and assume that the labor market network follows a Stochastic Block Model structure (Holland, Laskey, and Leinhardt 1983; Karrer and Newman 2011). In this setting, jobs are split into several blocks (markets), in which workers have a higher mobility probability. The detection of these blocks is done through the minimization of the likelihood function for the network generating process. This procedure captures markets by clustering jobs with large mobility patterns between them. This yields hundreds of labor markets, in which I assume that workers predominantly search for jobs.

With the labor markets defined, I can then assess how the structure and quality of firms in these markets affect individual wages. The general quality of the market can be proxied by a market-year fixed effect, which reflects how much that market contributes to wages in a given year. From a theoretical standpoint, this corresponds to the common outside option of all workers in that given market. In simpler terms, it can be thought of as the following: *If I lose this job and find another one in this market, I will earn at least this much.* There is, however, a second effect of market structure related to the fact that the worker can also search on the job for other opportunities in that market. This may lead to either a separation or wage renegotiation. Thus, the quality of all other potential employees in the market also matters. This is idiosyncratic since it depends on where each individual is working, and is therefore uncaptured by the market-year indicators. This term corresponds to the average of all other firms' quality in the labor market (proxied by the firm fixed effect) except the worker's own firm.

To estimate this set of parameters simultaneously, I take recent advancements in the peer effects literature that estimate the impact of peer quality on a given outcome in the presence of high-dimensional unobserved heterogeneity (Arcidiacono et al. 2012). This circumvents Manski (1993)'s reflection problem, as there is no potential reverse causality from the observed wage of individual i and the pay policies of other firms after controlling for worker and firm unobserved heterogeneity. The estimation procedure is a non-linear least squares version of the seminal Abowd, Kramarz, and Margolis (1999) model with three sets of high-dimensional fixed effects: worker, firm and market-year.

I start by characterizing market-year pay premia across several dimensions. These can be interpreted as how much a worker's wage would increase if she were to move to that market, keeping everything else constant. This implies that the identifying variation comes from two possible sources: 1) within-firm moves to other occupations or establishments; 2) market stayers in consecutive years. In fact, most of the variation in market pay premia is driven by occupation and time. Markets associated with occupations such as Managers, Skilled Professionals and Technicians pay between 0.05 and 0.2 log points more than those associated with other occupations. The differences across industries and regions are not as striking. The accommodation and food services industry is the worst-paying behind manufacturing, and the Lisbon region is the one where market premia are higher. Furthermore, I find that market effects drift, being stable during the 2010-2012 recessionary period and monotonically increasing afterwards. On average, the difference between pay premia in a market in 2021 versus 2010 is about 0.5 log points. Lastly, I find that high-wage workers tend to work in high-wage markets, although this positive sorting of workers to markets is unveiled only at higher tenures in the workforce. In other words, higher-ability workers have better outside options as they age in the labor market. This is an important finding, as it adds another dimension to labor market sorting that is usually not investigated, and shows how important general market structure can be in explaining wage determination.

Next, I investigate how the average quality of other firms in the market may impact a worker's wage. To do so, I start by summarizing the difference between the fixed effect of the current firm and the estimated leave-out average of firm effects, thus comparing how much more (or less), on average, the worker could get paid if she were to switch to any firm in the market at random. In fact, workers in higher wage percentiles would be worse off if they were to perform such a switch. The average gap between current and alternative firm premia for workers in the bottom 25th percentile is 0.07 log points, versus -0.13 log points in the top 10th percentile. This result could be an equilibrium outcome due to sorting, as higher wage workers have fewer better-paid alternatives than those at the bottom of the distribution. Interestingly, and in line with recent work on the impact of labor market power on wage markdowns (Jarosch, Nimczik, and Sorkin 2024), individuals in more concentrated labor markets also have worse alternatives. In a second exercise, I estimate the elasticity of wages to this leave-out average of firm effects. Given the presence of the market-year fixed effect, which "cleans" any unobserved common variation in market shocks, this elasticity is identified through differences in the structure of markets and through changes in the employment shares of firms in each market. The intuition is that if all firms in the market have the same size, then the variation in the value of outside employment is null. On the flipside, if firms have different sizes within a market, larger firms have a higher probability of being met and, thus, of hiring workers searching in the labor market. Thus, heterogeneity in the size of firms across markets and time generates variation that can be leveraged to identify the elasticity of interest. I find that, without market-year fixed effects, a 10% increase in the average quality of outside firms leads to an increase in wages of close to 3%. However, when controlling for common market-level shocks through the fixed effects, this elasticity drops to -0.1. This is because, without a measure that absorbs common shocks to outside options, the leave-out average of firm effects also captures the effect of local supply and demand shocks, which, as highlighted in the theory motivation above, affects the share of the outside option value that workers receive through bargaining. After controlling for market-year effects, however, what remains are idiosyncratic shocks that are either worker-firm specific or truly outside the firm. In this case, the quit/renegotiation channel dominates – firms mark down their offered wage to compensate for future wage increases due to competition. This elasticity is stronger for new hires, who, conditional on the firm, have better chances of being promoted in the future. This is also seen in the elasticity of separations and promotions to the (one-year) lagged value of the leave-out average of firm effects: both separations and promotions respond positively to an improved quality of outside firms.

How does this affect inequality? The work of Abowd, Kramarz, and Margolis (1999) (AKM) is influential in this regard, as it proposed a statistical model that attributes a large share of wage disparities to differences in worker ability, firm-specific policies and sorting. However, there are several sources of market frictions (Mortensen 2003) that contribute to wage disparities that are not captured in the AKM model, with the role of labor market structure and quality being one of them. To answer this question, I perform a variance decomposition of wages in the style of AKM to unveil how worker, firm and market unobserved heterogeneity may impact wage inequality in Portugal. Similar to AKM, the largest share of the wage variance is attributed to ability inequality (52%) and different firm pay policies (23%). However, a non-negligible 15% of the variance of real hourly wages is due to the variability in market-year effects. In other words, the fact that the same worker in the same firm may earn different wages depending on their labor market contributes almost as much to wage inequality as the variation in firms' pay policies. As for the idiosyncratic component of market structure, the heterogeneity in average quality of alternative firms is, in fact, inequality reducing, albeit negligible. Lastly, failure to consider the sorting between high wage workers to high wage markets inflates the contribution of worker-firm sorting to overall wage inequality, a finding that echoes recent work on the sources of inequality (Lamadon et al. 2024; Paula et al. 2025).

1.1. Related Literature

This paper contributes to several strands of the literature. The first concerns the measurement and estimation of the value of outside options, as well as their potential impact on affecting worker outcomes. The literature on this topic is still relatively recent. While cornerstone macroeconomic models of wage determination define the outside option of a worker as the value of non-employment (Pissarides 2000; Shimer 2010), recent evidence shows that wages may not be very sensitive to this object (Jäger et al. 2020). However, research has shown that other measures may have a direct impact on wages. Beaudry, Green, and Sand (2012) present a search and bargaining model of wage determination that considers workers' potential outside opportunities as the wages earned in their city across all industries except their own. Through a general equilibrium framework, this seminal work shows that industry composition variation across cities is closely related to average wage differences. Tschopp (2017) closely follows this strand, showing that, in Germany, a 10% increase in outside option wages generates a 7% own-wage increase. These papers rely on variation elicited by instrumental variables to isolate outside option changes from other possible confounders, such as aggregate demand. Schubert, Stansbury, and Taska (2024) focus instead on occupational mobility within a metro area to identify potential alternative wages. In this framework, a worker can leave their firm for another and remain in the same occupation, but may also switch occupations. Thus, the relevant alternative wages are a weighted average of within and between-occupation wages. Using a unique granular dataset on occupational transitions in the US, the authors estimate an elasticity of wages to outside options of close to 0.1. This method does not, however, account for the fact that historical occupational mobility does not reflect potential, unrealized moves. More recent literature has delved into proposing alternative ways to uncover this measure that account for unobserved heterogeneity and, therefore, correct this issue. Caldwell and Danieli (2024) derive a method from a matching model with two-sided heterogeneity, concluding that a 10% increase in a worker's alternative options leads to a 1.7% increase in wages, in Germany. Furthermore, some authors have shown that job-referral networks can impact labor market outcomes (Schmutte 2015). Following this, Caldwell and Harmon (2019) argue that coworker networks may be used to infer individual outside options. In this context, the authors find that, in Denmark, new openings at an individual's former coworkers' current firms lead to increased probability of job transitions and also lead to wage growth. Adjacently, a recent wave of studies has focused on investigating how workers perceive their outside options, with opposite conclusions. Jäger et al. (2024) also use coworker networks as a benchmark for potential wages in the event of job dismissal, finding that workers tend to underestimate their outside option value. However, using actual wage offers data in the U.S, Guo (2025b) reveals that workers tend to have accurate beliefs about the *average* potential wage *offered*. Using survey data from Germany, Caldwell, Haegele, and Heining (2025) reveal that the firm premia that workers expect from specific firms is highly correlated with the actual estimates of these firm premia, showcasing that workers do know about outside opportunities.

This work is also related to the monopsony literature, namely papers that study how competition for workers may influence wage markdowns. In their seminal contributions, Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006) present models of search and matching with auctions which show that firms may reduce hiring wages because they expect a steep wage schedule in the future. Through on-the-job search, workers present their current firm with alternative offers that induce competition between firms, leading to potential wage renegotiations (or separations). To insure against this, firms initially pay less than the match value to workers, generating a wage markdown. This form of monopsony power has more recently been introduced in interaction with amenities (Berger et al. 2024), market power (Jarosch, Nimczik, and Sorkin 2024) and has also been used to study wage sorting and inequality (Lamadon et al. 2024).

Third, we contribute to the peer effects literature. The reflection problem of Manski (1993) and Angrist (2014) is embedded in the estimation of outside option elasticities: if changes in the wages of firm A directly affect the wages in firm B and C, then this new wage in firms B and C may also affect the wages in firm A. The estimation of high-dimensional fixed effects models with peer effects is non-trivial. The methodology in Arcidiacono et al. (2012) is among the first to evade Manski's reflection problem in such a setting. More recently, Cornelissen, Dustmann, and Schönberg (2017) and Portugal et al. (2025) have used a non-linear least squares method to uncover the impact of co-worker ability on wages after controlling for worker and firm unobserved heterogeneity, while Baum-Snow, Gendron-Carrier, and Pavan (2024) use the same methodology to uncover local revenue and productivity spillovers at the firm level. This paper is the first to apply this empirical framework to study peer effects across workplaces.

Lastly, this paper adds to the vast literature on the determinants of wage inequality. Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013) have pioneered the use of high-dimensional fixed effects models to study the role of worker and firm unobserved heterogeneity in affecting wage inequality. These papers show that the largest share of wage variance is explained by differences in worker effects, meaning that individual-specific characteristics (e.g., ability) drive most of the observed wage inequality. Firm-specific pay premia also have a relative importance, as does the sorting of workers to firms. While these papers have estimated the additive two-way fixed effects model for France and Germany, it has been replicated in several countries: the United States (Song et al. 2019), Brazil (Alvarez et al. 2018), Italy (Macis and Schivardi 2016; Kline, Saggio, and Sølvsten 2020), Portugal (Card et al. 2018), and others (Bonhomme et al. 2023). The standard AKM model has more recently been extended to explore other potentially important sources of heterogeneity, such as job-title heterogeneity (Torres et al. 2018), time-varying firm premia (Lachowska et al. 2023) or origin-firm heterogeneity (Di Addario et al. 2023). This paper investigates the role of another driver of inequality aside from who you are and where you work – where you could work should you leave your firm. By affecting wage and mobility decisions, the sorting of workers to different labor markets can be an important driver of wage inequality dynamics in Portugal.

1.2. Roadmap

This paper is split into seven sections. Section 2 showcases a model that motivates the empirical exercise. Section 3 presents the data used. The statistical model and econometric framework are higlighted in Section 4, with estimation results in Section 5. In Section 6, I present the results on the impact of outside options on inequality. Lastly, Section 7 concludes with a summary of the results, future research and policy implications.

2. Theoretical motivation

The models that motivate this work are derivative of Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006). In essence, these present labor markets where firms post vacancies and workers search on the job for new offers. Upon meeting an offer, workers decide whether to take that offer by taking it to their employer, which triggers a renegotiation phase that mimics a second-price auction. In the end, workers either move to a new firm that offers a better contract or stay in their current firm with a renegotiated wage. Importantly, wages are initially set through Nash bargaining, granting workers some share of the match surplus.

To better approximate the reduced form model employed in this paper, consider a variation of this framework with a finite number of firms. This setting, borrowed from Jarosch, Nimczik, and Sorkin (2024) and Berger et al. (2024), generates firms with different discrete sizes, with workers being more likely to meet larger firms during search. Furthermore, consider that employees partially direct their search while on the job, as they do not consider positions in their current employer. These ingredients create within- and between-market bargaining positions and outside options. Wages depend on a weighted average of the match surplus of working at each firm in the market.

Wage equation The wage equation from Berger et al. (2024) is a good motivating example of the dynamics that this paper wants to capture[1]:

$$w_i(\sigma) = \sigma z_i + (1-\sigma)b + \beta\Bigg[(1-\sigma)\theta\sum_k \lambda_{uk}\max\{S_k, 0\} - \tag{1}$$

[1]For exposition purposes, this version of the equation ignores non-wage amenities

$$- \sum_{k \neq i} \lambda_{ik} \max\left\{0, \min\left\{(1-\sigma)\theta(S_k - S_i), (S_k - S_i)\right\}\right\} + (1-\sigma)S_i \Bigg]$$

where $w_i(\sigma)$ is the wage of worker in firm i as a function of the match surplus share, σ; z_i is the productivity of the firm she works for; b is the flow value of unemployment; θ is the bargaining power of the worker; λ_{ik} is the meeting rate between a worker in firm i and a vacancy in firm k; S_i is the match surplus of working in firm i.

In this setting, workers get:

a. Part of the match productivity: σz_i;
b. A share of their outside option: $(1-\sigma)\left(b + \beta\theta \sum_k \lambda_{uk} \max\{S_k, 0\}\right)$;
c. A (negative) compensating differential from quits/renegotiation: $\beta \sum_{k \neq i} \lambda_{ik} \max\{0, \min\{(1-\sigma)\theta(S_k - S_i), (S_k - S_i)\}\} + (1-\sigma)S_i$.

This shows that the wage policies of other firms can directly influence wages through channels b) and c). First, workers, once they find a job, negotiate their wage in a Nash bargaining setting and get some share of the match surplus; second, due to positive future wage increases stemming from on-the-job search and bargaining, firms tend to downgrade wages at earlier tenures. This steepness of the wage schedule generates a form of monopsony power and generally depresses wages. Empirical exercises that estimate the impact of outside options on wages generally fail to disentangle these mechanisms. This paper addresses both channels from a reduced-form approach, highlighting the importance of the outside option and the quit/renegotiation channels in determining wages.

3. Data

I use Quadros de Pessoal (QP, Lists of Personnel), a unique matched employer-employee administrative dataset sourced from the Ministry of Employment and Social Security. This is a mandatory survey filled in by every establishment having at least one wage-earner, containing information on virtually the universe of private Portuguese firms and their employees. The survey is responded to in October of each year (March prior to 1993). The years available are 1986-2021, with gaps for 1990 and 2001, although the estimation considers only the period 2010-2021. Being a compulsory annual survey, it ensures that problems such as panel attrition are minimzed. Furthermore, measurement error, missing values and misclassification issues are also rare due to its handling by the Portuguese authorities. Notwithstanding, this is a survey of employer firms: it does not include information on civil servants, self-employed or the unemployed. Its coverage of the agricultural and fisheries industries is also lacking due to the high prevalence of self-employed and informal work.

Each firm entering the database is assigned a unique identifying number, allowing researchers to track the same firm over time. Each worker is also identified with a unique number, enabling the matching of workers to firms. It is, therefore, possible to build a worker's employment history as long as they remain employed by firms targeted by the survey.

The dataset contains information about the firm's industry, sales, employment, location, ownership, and legal status. It also provides information on establishments, which are the smallest units belonging to a firm that can employ workers, and can be linked to employees with a unique identifier. This is important to define relevant labor markets given the potentially geographical distance between a firm's headquarters and an employee's workplace. For example, a firm headquartered in Lisbon can have several establishments across the country. Failure to account for this would lead us to conclude that some employees' relevant labor market would be based in Lisbon, whereas they may be in other parts of the country. Data on workers includes monthly wages (including base, overtime, and supplements), hours worked (regular and overtime), demographics (age, gender, education, nationality), occupation (ISCO 4-digit), and starting date with the firm.

I employ some restrictions on the dataset to identify and estimate the model of interest. First, the final sample was restricted to full-time workers aged 18-64 who earn at least 80% of the national minimum wage. This threshold is motivated by the fact that in the Portuguese labor market, apprenticeships may collect 80 percent of the minimum wage. Second, only workers in the services and manufacturing sectors were included, implying the exclusion of those working in agriculture, fisheries, energy, and extraction sectors. Third, for estimation purposes, only peer groups (defined in the next section) with more than two firms and workers are kept. Lastly, I exclude workers and firms not belonging to the largest three-way connected set between worker, firm and peer group. This latest exclusion restriction is needed for the identification of firm and peer fixed effects, which are only comparable between firms and peer groups linked by mobility (see Section 4.3.1 for details). The last two steps are done in an iterative manner to ensure all the exclusion restrictions are met in the final dataset.

Overall, the final sample includes 16,064,983 observations, corresponding to 3,249,865 workers and 203,304 firms. Based on the aforementioned restrictions, this sample's observations correspond to 68% of the original dataset.

4. Methodology

4.1. A stochastic block model for detecting labor markets

To detect relevant labor markets for workers, I use a degree-corrected stochastic-block model approach (Holland, Laskey, and Leinhardt 1983; Karrer and Newman 2011), a tool from the community detection literature that classifies nodes in a multigraph network into groups based on the probability of edges occurring between them. This tool can be applied in the context of labor markets, where workers or firms are assigned into "markets" based on mobility patterns across establishments and occupations. This has been used by Nimczik (2020) to identify "data-driven labor markets" based on job mobility networks in Austria. In this paper, the nodes of the network are jobs, which are defined as an establishment × occupation pair. The reasons for this choice are threefold. First, I use establishments instead of firms because these better capture the geographical aspect of the workplace, which can be one of the most important factors driving mobility decisions. For instance, a worker may be employed by a firm that is headquartered in Lisbon and that holds several establishments across the country, with her place of work being in Algarve. In this case, her relevant alternative choices of employment are other establishments in the Algarve region instead of Lisbon. Second, occupation is also an important factor to consider. Not only has it been used to infer workers' outside options (Schubert, Stansbury, and Taska 2024), but, when considered jointly with the establishment information, it provides a better a better approximation of workers' social networks. Within an establishment, workers are more likely to perform tasks in teams of workers with the same occupation, thus creating stronger ties with those co-workers. As shown in Eliason et al. (2023), the sorting of workers to establishments is highly impacted by workers' social networks, and past co-worker networks have also been used to infer outside options (Caldwell and Harmon 2019). Third, from a technical standpoint, having a stricter definition of a labor market is useful for obtaining useful identifying variation from the data. Thus, the network considered in this exercise will be one where nodes are establishment × occupation pairs (which I call jobs) and edges are drawn according to mobility between those nodes.

Consider the following network formation model. There are J jobs, $j = \{1, \ldots, J\}$. Each job is inserted in a market m, $m = \{1, \ldots, M\}$. Workers move between jobs, either within or across markets. Let z_j denote the assignment of job j to its market, $z_j \in \{1, \ldots, M\}$. Consider the adjacency $J \times J$ matrix $\mathbf{A}$, whose entries A_{pq} are equal to the number of workers moving from job p to q. Consider also the $M \times M$ matrix $\mathbf{B}$, where B_{uv} represents the probability of moving from a job in market u to market v. Jobs within each market are structurally equivalent, i.e. workers face the same probability distribution of moving across jobs within each market, which equals $B_{m,m}$. Notwithstanding, some jobs are more "desirable" than others and can attract more workers. On the other hand, some jobs have a high level of separations and dispense more workers. This attractiveness is given by γ_j^+ and γ_j^-, respectively. As such, the expected number of workers moving from job p to q is given by $E[A_{pq}] = \gamma_p^- \gamma_q^+ B_{z_p z_q}$, where z_p and z_q are the markets of job p and q, respectively.

ASSUMPTION 1. *Job offers arrive according to a Poisson process with rate γ_j^-.*

It can be shown that $A_{pq} \sim Poisson(\gamma_p^- \gamma_q^+ B_{z_p z_q})$. The goal is, given the mobility patterns observed, to infer the structure of the job mobility network, **G**. Therefore, the likelihood function for the network generating process of this model is:

$$\mathcal{L}(\mathbf{G} \mid \mathbf{B}, \mathbf{z}, \gamma^{+}, \gamma^{-}) = \prod_{p,q} \frac{(\gamma_p^{-}\gamma_q^{+}B_{z_p z_q})^{A_{pq}}}{A_{pq}!} \exp(-\gamma_p^{-}\gamma_q^{+}B_{z_p z_q}) \tag{2}$$

The objective is to choose assignments of jobs to markets that maximize (2). To do this, I employ the MCMC approach in Peixoto (2014) that explores different combinations of assignments and chooses the structure that minimizes the entropy of the model.

4.2. Defining relevant outside options

After classifying jobs into markets, it is then possible to define workers' relevant alternative options, and thus understand the impact of the job network structure on wages.

Starting from the markets defined in the previous section, I delimit the job outside options for a given worker to the establishments in those markets that have at least one worker with the same occupation in a given year. To put it differently, consider worker i, working in establishment e, with occupation o. This establishment × occupation pair belongs to market m. So, the worker's job outside options are jobs in all the establishments of market m that have at least one worker with occupation o. This assumption implies that workers only receive offers from those establishments and, therefore, do not move across markets or occupations. While this is not realistic in the data, it helps pin down the relevant network structure in a parsimonious way.

4.3. A peer effects perspective of outside options

To investigate the role of market quality on wages, I employ a peer effects framework, extending the usual two-way fixed effects equation of AKM to accommodate the impact of other firms' pay policies on wages. Consider the following model:

$$w_{ifmt} = \boldsymbol{\beta}\mathbf{x}_{ifmt} + \alpha_i + \zeta_f + \gamma\overline{\zeta}_{-fmt} + \varepsilon_{ifmt}, \tag{3}$$

where w_{ifmt} is worker i's wages in firm f, market m at time t; α_i is the worker's ability or unobserved heterogeneity; ζ_f is her firm's pay policies; $\overline{\zeta}_{-fmt}$ is average of all other firms' fixed effects for market m at time t; and ε_{ifmt} is an idiosyncratic shock. In this framework, the object $\overline{\zeta}_{-fmt}$ is capturing a worker's outside options via the average of what she could get should she decide to randomly search – and accept – a job in that market. However, from the wage equation posited in section 2, it can be inferred that this object is capturing different dynamics. First, it can be including common shocks to the labor market, which could also affect all firms equally and change a worker's value of unemployment and, therefore, their outside option. This has a positive effect on wages if workers gain some share of the match surplus. This is not, however, an effect stemming from an improvement of job conditions outside of the workers' firm, as the outside option is better because the market dictates so. Second, it may also be capturing shocks to particular firms or segments of the market, i.e. shocks that are truly outside the firm. This second step changes what the worker could get from future bargaining and renegotiation, which may have a positive or negative effect on current accepted wages, depending on which is stronger: worker bargaining power or the markdown imposed due to a steeper future schedule. Thus, any reduced-form model that estimates a parameter such as γ in (3) is bound to conflate several links between outside options and wages.

To counteract this, on top of the worker and firm effects, I add market-by-year fixed effects, which capture any common shocks to the labor market that may affect a worker's wage. The relevant equation is

$$w_{ifmt} = \boldsymbol{\beta}\mathbf{x}_{ifmt} + \alpha_i + \theta_{mt} + \zeta_f + \gamma\bar{\zeta}_{-fmt} + \varepsilon_{ifmt}, \tag{4}$$

where θ_{mt} is a market-year fixed effect. This object captures any common market-level shocks that may affect the worker's outside option, as posited above. Hence, $\bar{\zeta}_{-fmt}$ now reflects the market quality that is truly outside the firm. This can also be thought of as the opportunity cost of working at firm f *vis-à-vis* all other firms in the market since, by choosing firm f, worker i is foregoing current opportunities in all other firms in the market. Lastly, this measure is also tied to the quit/renegotiation channel mentioned in the previous sections: on-the-job search implies that the worker will get offers from her alternative options, which has a potential impact on her contract as she might renegotiate future wages based on those offers. Therefore, firm f may actually pay lower wages today, already accounting for future job surplus deterioration stemming from renegotiation. This leads to compensating wage differentials in the vein of Postel-Vinay and Robin (2002).

4.3.1. Identification

There are two main sets of objects that grant an identification discussion, the high-dimensional fixed effects (HDFEs), α, θ and ζ, and the parameter concerning the elasticity of wages to other firms' pay policies, γ. Consider the following assumptions:

ASSUMPTION 2. ***Exogenous mobility***.

Let $f(i,t)$ and $m(i,t)$ denote the firm and market assignment of worker i at time t. Let $\omega_{m(i,t)} = \{\omega_1, \dots, \omega_F\}$ be the set of weights given to each of the F firms in market $m(i,t)$. Lastly, let $\Omega_i = \{\alpha_i, f(i,t), m(i,t), X_{it}, \omega_{m(i,t)}\}_{t=0}^{T_i}$. Then, for the set of error terms $\varepsilon_i =$

$\{\varepsilon_{i,m(i,1),f(i,1),1} \cdots \varepsilon_{i,m(i,T_i),f(i,T_i),T_i}\}$

$$\mathbb{E}\left[\varepsilon_i \mid \Omega_i\right] = 0 \tag{5}$$

This is a standard strict exogeneity assumption which, in the context of AKM models, is also denominated as an exogenous mobility assumption. It states that the wage errors, ε_i, should have an expected value of zero conditional on worker type, firm and market assignment, covariates and other firms' weights (used in the leave-out average firm effect). This is an important assumption that restricts mobility decisions to be uncorrelated with firm- or market-match effects. At the same time, this does not rule out any effects of worker, firm or market on mobility decisions. It may still be possible that high α workers move more frequently than low α ones, or that they move to firms with higher premia than their counterparts.

ASSUMPTION 3. ***Additivity***

There are no interactions between worker, firm and market fixed effects. There are no other worker, firm or market-specific characteristics that systematically affect wages.

This assumption rules out match-specific effects in which any interactions between the fixed effects is relevant. In a potential outcomes framework, it is equivalent to saying that the potential outcomes from working at firm f and market m equal the sum of the potential outcomes of firm f and market m.

Given the stated assumptions, the identification argument for α, θ and ζ is similar to that of Abowd, Creecy, and Kramarz (2002) but with an extra set of fixed effects.

DEFINITION 1. *Consider three-way tuples of worker, firm and market-time (w, f, mt). Two tuples are* ***nearly identical*** *if they are similar in all but one element of the tuple.*

For the HDFEs to be identifiable, we need to prune the data to the set of three-way tuples (worker, firm, market-time) that are nearly identical. For example, the tuples (worker 1, firm 1, market-time 1) and (worker 2, firm 1, market-time 1) are nearly identical. By classifying all the tuples iteratively, it is possible to create sets of tuples that are connected by this definition. I follow Weeks and Williams (1964) and Stata's *group3hdfe* command (Guimaraes 2016) to identify the largest connected set of tuples that grants identification of the fixed effects. Notice that, contrarily to an AKM argument, identification is not solely obtained from those switching firms or markets due to the time dimension of the third set of fixed effects. Thus, a worker may not change firm or market and still contribute to the identification of these effects, in a fashion similar to Lachowska et al. (2023).

Next, we have the identification of γ. This is obtained through changes in the job network composition, i.e. variation in the peer groups' composition. Notice that $\bar{\zeta}_{-fmt}$ can be either a weighted or an unweighted average of firm effects. Consider first the unweighted form:

$$\bar{\zeta}_{-fmt} = \frac{\sum_{j\in mt}\zeta_j - \zeta_f}{N_{mt}-1} \tag{6}$$

The inclusion of θ_{mt}, the peer group fixed effects, absorbs the variation in $\frac{\sum_{j\in mt}\zeta_j}{N_{mt}-1}$. Thus, after the inclusion of the firm effects, the identifying variation comes solely from the denominator in $-\frac{\zeta_f}{N_{mt}-1}$. Hence, γ is only identified when new firms start or close operations in different markets. In a static economy, with no firm entry and exit, γ would not be identified.

The same principle applies if the weighted average form is used:

$$\bar{\zeta}_{-fmt} = \frac{\sum_{j\in mt}\omega_{jt}\zeta_j - \omega_{ft}\zeta_f}{1-\omega_{ft}} \tag{7}$$

where ω_{jt} is the weight of firm j at time t. The first part of the subtraction, $\frac{\sum_{j\in mt}\omega_{jt}\zeta_j}{1-\omega_{ft}}$ is absorbed by the peer effects if all firms in the market have the same weight, and the only variation remaining derives from $-\frac{\omega_{ft}}{1-\omega_{ft}}$. In this case, identification is possible due to different market structures and changes in the weights over time. In this paper, I use employment weights, thus identification is enabled by heterogeneous firm sizes and worker accessions or separations from the firms in the peer group, changing the relative employment weight of firm f in market m.

4.3.2. Matrix Form

To understand how one can estimate (4), it is best to resort to matrix algebra, as in Portugal et al. (2025). Let us consider a balanced panel for exposition purposes. There are N workers, T periods, F firms, M groups (i.e. markets), and K covariates.

a. $\mathbf{W}$ is the $NT \times 1$ matrix of worker wages;
b. $\mathbf{D}_w$, $\mathbf{D}_f$ and $\mathbf{D}_{mt}$ are the $NT \times N$, $NT \times F$ and $NT \times MT$ worker, firm and market-time design matrices, respectively;
c. α, ζ and θ are the $N \times 1$, $F \times 1$ and $MT \times 1$ worker, firm and market-time fixed effects matrices, respectively;
d. $\mathbf{V}$ is a matrix that creates leave-out averages when right-multiplied by any matrix. We can think of V as a block-diagonal matrix composed by sub-matrices for each group g that create the leave-out averages;
e. $\mathbf{X}$ is the $NT \times K$ matrix of covariates;

Then, equation (4) can be written as

$$\mathbf{W} = \mathbf{X}\beta + \mathbf{D}_w\alpha + \mathbf{D}_{mt}\theta + \gamma\mathbf{V}\mathbf{D}_f\zeta + \mathbf{D}_f\zeta + \varepsilon \tag{8}$$

$$\mathbf{W} = \mathbf{X}\beta + \mathbf{D}_w\alpha + \mathbf{D}_{mt}\theta + [\gamma\mathbf{V} + \mathbf{I}]\,\mathbf{D}_f\zeta + \varepsilon \tag{9}$$

4.3.3. Toy example

To better visualize (9), consider the following example with 6 workers, 3 firms, 2 markets and only one time-period. For simplicity, let us ignore the covariates and market matrices. In this example consider that

a. Workers 1 and 2 work in Firm 1 and belong to the same market (M_1);
b. Worker 3 is in Firm 2 and belongs to market M_1;
c. Workers 4 and 6 are in Firm 3 and in market M_2;
d. Worker 5 is in Firm 2 but in market M_2;

Thus, in this example, market M_1 includes firms 1 and 2, and market M_2 includes firms 2 and 3. Hence, Firm 2 spans two different markets, so peer groups are not disjoint. In this case, the matrices would be

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{D_w}} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \end{bmatrix} + \left(\gamma \underbrace{\begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1/2 & 1/2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{\mathbf{V}} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \right) \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{D_f}} \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix} + \varepsilon$$

4.3.4. Estimation

Let $\mathbf{e} = \left(\mathbf{W} - \mathbf{X}\hat{\beta} - \mathbf{D}_w\hat{\alpha} - \mathbf{D}_{mt}\hat{\theta} - [\hat{\gamma}\mathbf{V} + \mathbf{I}]\,\mathbf{D}_f\hat{\zeta}\right)$ be the vector of residuals. To estimate (4), we need to solve the non-linear least squares problem

$$\min_{\hat{\beta},\hat{\alpha},\hat{\theta},\hat{\gamma},\hat{\zeta}} \mathbf{e}\mathbf{e}'$$

The first-order conditions from this problem are

$$\frac{\partial \mathbf{ee}'}{\partial \hat{\beta}} = \mathbf{0} \Leftrightarrow \mathbf{X}'\mathbf{e} = \mathbf{0} \tag{10}$$

$$\frac{\partial \mathbf{ee}'}{\partial \hat{\alpha}} = 0 \Leftrightarrow \mathbf{D}_w'\mathbf{e} = \mathbf{0} \tag{11}$$

$$\frac{\partial \mathbf{ee}'}{\partial \hat{\theta}} = 0 \Leftrightarrow \mathbf{D}_{mt}'\mathbf{e} = \mathbf{0} \tag{12}$$

$$\frac{\partial \mathbf{ee}'}{\partial \hat{\gamma}} = 0 \Leftrightarrow \hat{\zeta}'\mathbf{D}_f'\mathbf{V}'\mathbf{e} = \mathbf{0} \tag{13}$$

$$\frac{\partial \mathbf{ee}'}{\partial \hat{\zeta}} = 0 \Leftrightarrow \left(\hat{\gamma}\mathbf{D}_f'\mathbf{V}' + \mathbf{D_f}'\right)\mathbf{e} = \mathbf{0} \tag{14}$$

As in Arcidiacono et al. (2012) and Portugal et al. (2025), I reiterate that (14) is hard to compute given the high dimensionality of the problem. Thus, let us re-write the equation so that it is easier to solve for in an iterative process:

$$\left(\hat{\gamma}\mathbf{D}_f'\mathbf{V}' + \mathbf{D_f}'\right)\mathbf{e} = \mathbf{0} \Leftrightarrow \tag{15}$$

$$\mathbf{D}_f'\left(\hat{\gamma}\mathbf{V}' + \mathbf{I}\right)\mathbf{e} = \mathbf{0} \Leftrightarrow \tag{16}$$

$$\mathbf{D}_f'\left(\hat{\gamma}\mathbf{V}' + \mathbf{I}\right)\left(\mathbf{W} - \mathbf{X}\hat{\beta} - \mathbf{D}_w\hat{\alpha} - \mathbf{D}_{mt}\hat{\theta} - \left[\hat{\gamma}\mathbf{V} + \mathbf{I}\right]\mathbf{D}_f\hat{\zeta}\right) = \mathbf{0} \Leftrightarrow \tag{17}$$

$$\mathbf{D}_f'\left(\hat{\gamma}\mathbf{V} + \mathbf{I}\right)'\left(\mathbf{W} - \mathbf{X}\hat{\beta} - \mathbf{D}_w\hat{\alpha} - \mathbf{D}_{mt}\hat{\theta}\right) = \mathbf{D}_f'\left(\gamma\mathbf{V} + \mathbf{I}\right)'\left(\hat{\gamma}\mathbf{V} + \mathbf{I}\right)\mathbf{D}_f\hat{\zeta} \tag{18}$$

Thus, given some initial vector $\hat{\zeta}_0$, we can iteratively solve the minimization problem. For the h iteration:

a. Given $\hat{\zeta}_{h-1}$, obtain $\hat{\beta}_h$, $\hat{\alpha}_h$, and $\hat{\gamma}_h$ through OLS;
b. Given a., solve (18) to get $\hat{\zeta}_h$
c. Repeat until some convergence criterium is met.

4.3.5. Bias correction

Estimating a non-linear model with many high-dimensional fixed effects suffers from incidental parameter bias (Neyman and Scott 1948). This bias arises from the measurement noise in estimating the fixed effects, which only vanishes for long enough panels, i.e. $T \to \infty$. To overcome this issue, I implement the bias correction method in Dhaene and Jochmans (2015), which is based on a split-sample jackknife procedure. To do this, I estimate the model not just using the full panel, but also by splitting the sample into two half-panels and using them to re-estimate the model. Afterwards, I take the half-panel estimates to adjust the bias in the full-panel model.

More specifically, consider the set of estimates from estimating model (4) using the whole sample, $\hat{\Theta}_{full}$. Then, let us take the full sample and, for each worker, divide their work history into two half-panels. This implies that each worker should have at least three periods of observations, ideally four. After, estimate again the model, sourcing, instead, the data from each half-panel separately. This yields two extra sets of coefficients, one for each half-panel: $\hat{\Theta}_1$ and $\hat{\Theta}_2$. Then, according to Dhaene and Jochmans (2015), an unbiased estimate for Θ, $\hat{\Theta}_{unb}$, can be obtained as:

$$\hat{\Theta}_{unb} = 2\hat{\Theta}_{full} - \frac{1}{2}\left(\hat{\Theta}_1 + \hat{\Theta}_2\right) \tag{19}$$

The covariance matrices for $\hat{\Theta}_{unb}$ are the average of the half-panel estimated matrices.

5. Results

5.1. Markets summary statistics

The estimation of the job mobility network in (2) yields, for each establishment-occupation pair (i.e., job), a market assignment. Table 1 highlights the summary statistics of this process, estimating a total of 688 markets across the country, with each market having, on average, 615 firms. Firms may be present in more than one labor market, either because they are a multi-establishment firm or because they employ workers across several occupation groups. This is reflected in the summary statistics: firms participate, on average, in 15.3 markets and they have 19.3 average workers in each of these markets. Lastly, 37% of workers who switch firms do so within their market, a percentage that goes up to almost 50% if, instead, we consider moves across establishments. These percentages may seem low, but it is important to recall that the SBM's objective function maximizes job-to-job flows within markets, not the firm-to-firm or establishment-to-establishment flows[2]. Workers who move within establishments but to another occupation are considered to be job movers in the model, and the same is true for workers who move within firm but across establishments. Thus, it is not surprising nor problematic that the model estimates these flow percentages.

5.2. Firm and market effects

Distributions Figure 1 shows the distributions of $\hat{\zeta}$ and $\hat{\theta}$, i.e. the firm and market-time effects, respectively. Given that these effects are identified up to a constant, the literature usually normalizes them to enable a potential interpretation. The firm effects

[2] In fact, the share of job-to-job flows (i.e., establishment-occupation to establishment-occupation flows) that occur within a market is 68%. In matrix terms, this represents the trace of the matrix that contains the probability of moving between blocks in the SBM, which I denoted **B** in section 4.1.

TABLE 1. Markets summary statistics

Statistic	Value
Number of markets	688
Average firms per market	614.8
Average firm size per market	19.3
Average markets per firm	15.3
Firm-firm flows within market	37.0%
Establishment-establishment flows within market	48.7%

Notes: All statistics refer to the year of 2021 with the exception of the last two rows, which are obtained from the whole sample.

are normalized such that the average of the Accommodation and Food Services industry – a sector with low firm premia – is zero, while the market-time effects are normalized such that the average of the 2010 effects is zero. The figure shows a rather symmetric firm effects distribution that closely mimics a Gaussian with the same mean and standard deviation. The average firm pays a positive premium relative to the Accommodation and Food average, despite the close symmetry around this average. There is a higher concentration of firms around the mean of the distribution *vis-à-vis* the Gaussian, but, overall, the distribution of the firm effects is well-behaved. The market-time effects distribution, on the right, shows that, for most of the distribution, markets pay a positive premium relative to the 2010 average, reflecting the recessionary period that the country was facing around this time. This distribution has a longer right-tail, which is also mirrored in its positive skewness, indicating the presence of a non-negligible number of high-paying markets in the economy. As seen in Figure 2, markets with larger premia are usually also associated with high-paid occupations and industries. Managers, skilled professionals and technicians and associate professionals top the rank of professions with the highest market-year fixed effects, with their premia reaching almost double that of the remaining occupations. When looking at industries, those usually associated with higher value-added activities, such as information and communication, finance, and consulting activities present the largest premia, while the accommodation and food industry shows the lowest. As for location – here proxied by NUTS II – there is a higher premium for markets in the Lisbon area, followed by the North and Center and with Alentejo and Algarve at the bottom. The Lisbon area has a high concentration of high-value-added services and professionals, so it is intuitive that it should have the largest market premia. By contrast, the poorer regions of Alentejo and Algarve are highly dependent on low-value-added jobs such as those in hotels and restaurants, so it is also natural that their market premia are also lower.

The breakdown by occupation, sector and location shows that occupation plays an important role in determining market premia over other characteristics, such as location.

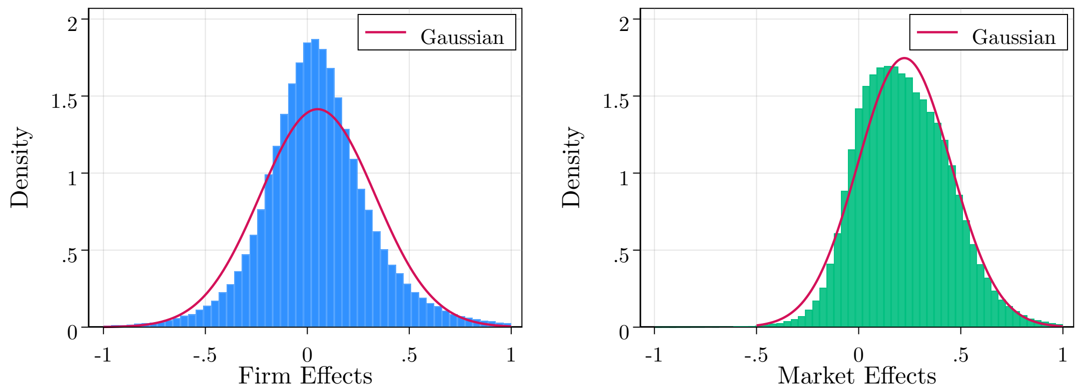


FIGURE 1. Fixed effects distributions

The highest-paid markets will not necessarily be the ones in "better" locations, but instead the ones for "better" occupations. In other words, what one does is more important for wage determination than where the firm is located or which industry it operates in. This vindicates the results in Torres et al. (2018), who show that one fifth of the wage variation in Portugal is due to the variation in job titles (a finer definition of occupation) premia.

Do market effects drift? Given the time dimension captured in θ, a natural question arises: how do market effects evolve over time? Previous work has shown that firm effects have a relatively large autocorrelation, implying that firms' pay premia are rather sticky (Lachowska et al. 2023). In the case of market effects, the conclusions are different. Figure 3 shows two panels that dissect the time-varying behavior of market effects. They show, for a balanced panel of markets present in the 12 years of the sample, that markets' pay premia have shown a positive trend over time. The first panel, which is also replicated by industry in Figure 10, presents a scatter plot of the market effects in 2010 vs. 2021. In general, those in 2021 are larger than in 2010, with stronger deviations for firms at the very bottom and at the very top of the 2010 distribution. Panel B shows the trend for the average market, with 2010 being equal to zero. Interestingly, market effects are sticky at the beginning of the period, with the recession years showing little improvement in the pay premia of markets. The positive trends start to pick up after 2013, right before the Portuguese economy also starts improving. By 2021, on average, markets were paying 0.5 log points higher wages than in 2010.

Sorting Another relevant question that arises from this setup is how workers sort across firms and markets. From the inequality literature, much is known about worker-firm sorting. In general, it has been shown that high-wage workers tend to work for high-

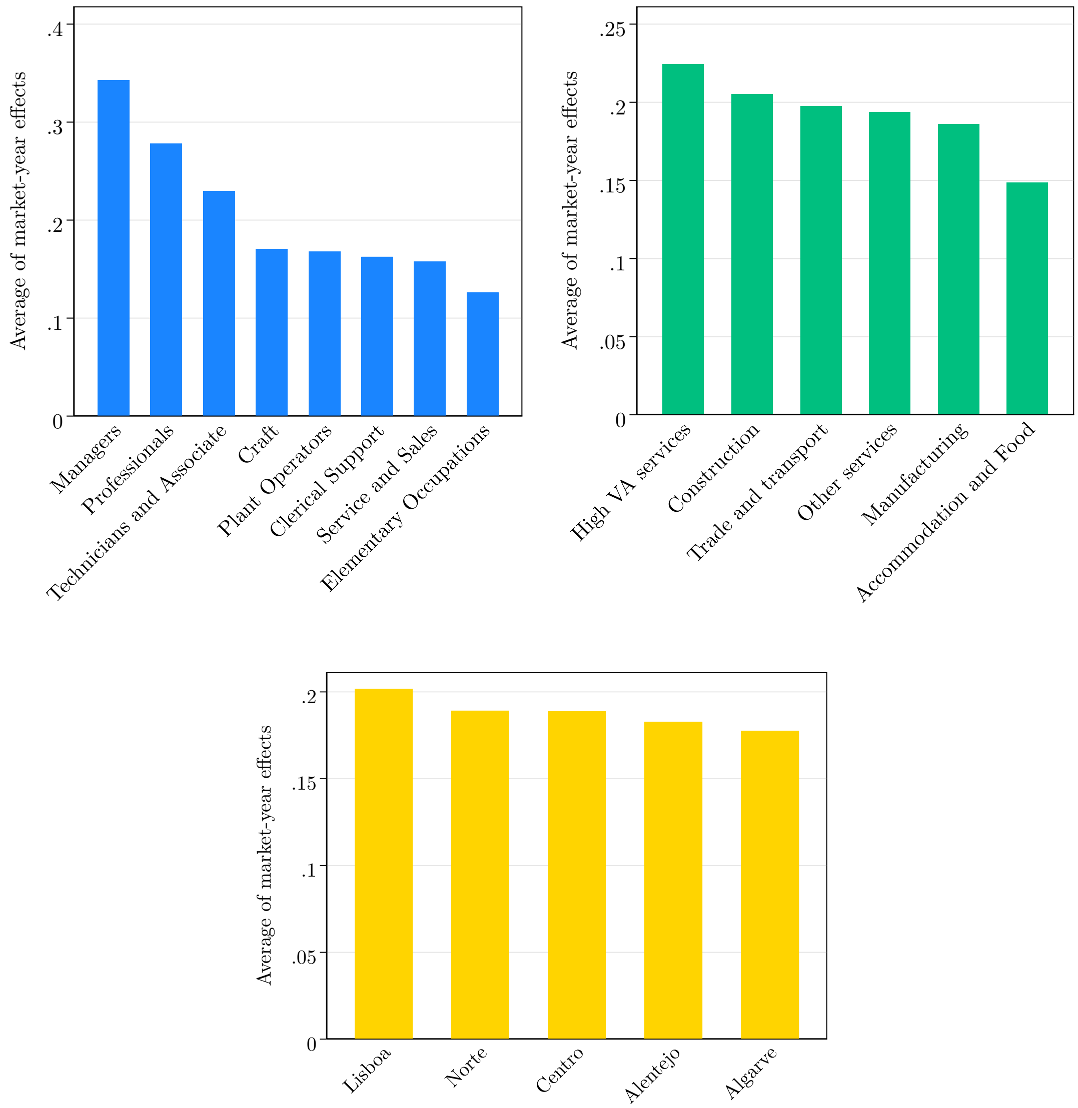
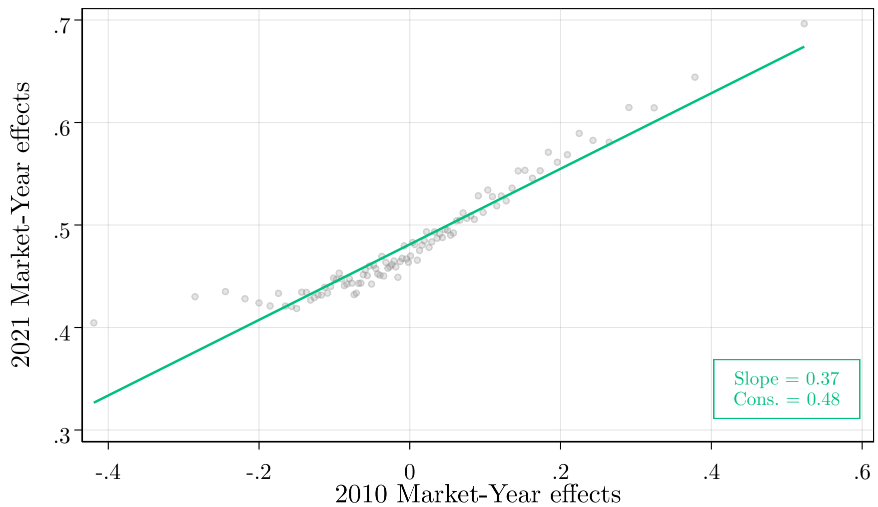


FIGURE 2. Average market-year fixed effects

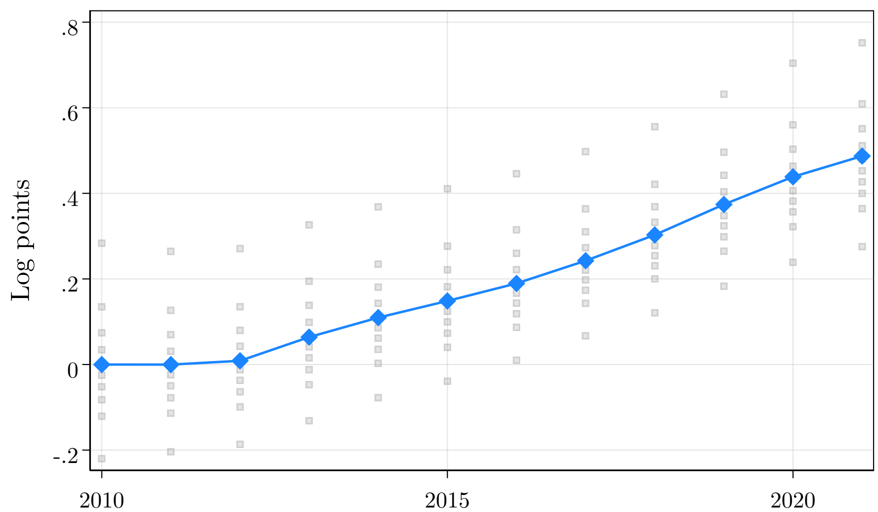
Note: Left panel: average of market-year fixed effects by 1-digit ISCO occupation code. Right panel: average of market-year fixed effects by industry or group of industries. High VA services = Information and Communications; Financial Services; Real Estate Activities; Professional, Scientific and Technical Activities. Market-year fixed effects normalized such that the sample average in 2010 is zero.

premium firms, although some studies show that sorting can be dynamic and change along the job market tenure dimension or as workers age (Lentz, Piyapromdee, and Robin 2023; Lamadon et al. 2024).

The left panel of figure 4 shows a bivariate density plot, with worker fixed effects deciles on the y-axis and firm fixed effects deciles on the x-axis. Each square's color represents the number of workers in that given worker-decile × firm-decile combination. A darker color



A. 2010 vs. 2021



B. Average market effects over time

FIGURE 3. Dynamics of market effects

Note: Market-year effects normalized such that the average of 2010 effects is zero. Estimated on a balanced sample for all firms present in all 12 years of the sample. Panel B shows the average of market effects weighted by number of employees in the market.

indicates a larger number of workers in the square. In line with previous studies, the left panel shows that there is a positive correlation between high-wage workers and high-wage firms. The correlation is particularly strong in the top 2 deciles of each distribution. This positive correlation between worker and firm effects is not necessarily a feature of every labor market, since high-wage firms do not necessarily yield a higher surplus for workers if workers have a strong preference/distaste for non-wage job-specific characteristics (Rosen

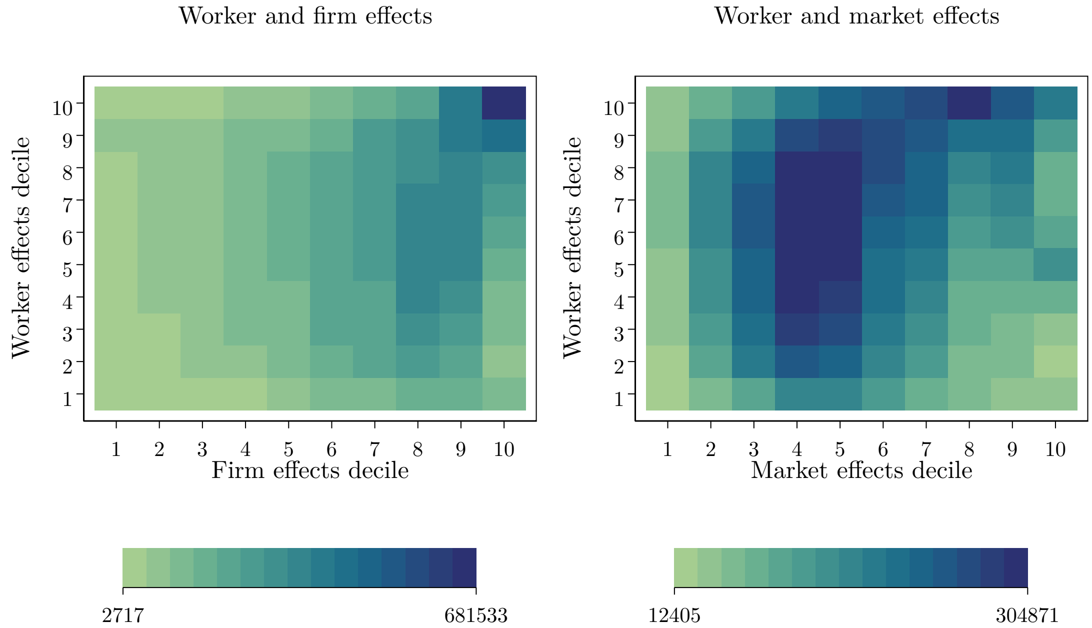


FIGURE 4. Correlation between fixed effects

1986), if there are labor market frictions (Mortensen 2003), or if there are compensating differentials from search-and-bargaining channels (Postel-Vinay and Robin 2002).

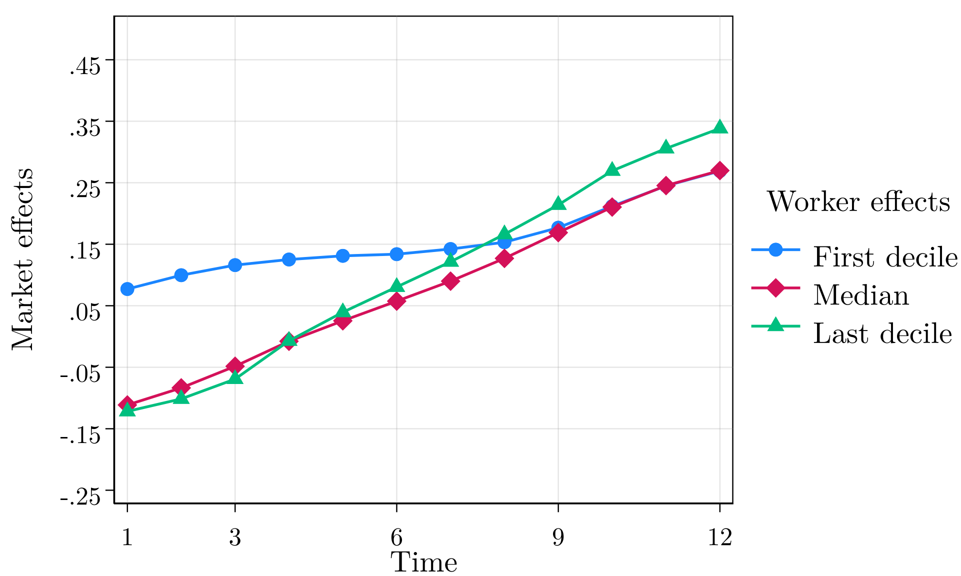


FIGURE 5. Market fixed effects over time, by worker fixed effect decile

The right-hand side panel shows a similar bivariate plot, but where the x-axis has the deciles of the average market-year fixed effects average over years, i.e., with only one fixed effect per market. The picture is strikingly dissimilar from the previous one. In this case, workers with fixed effects in the upper deciles are not necessarily working in markets with high fixed effects. There seems to be a concentration around the median, where the density of the bivariate distribution accumulates. This, plus the slightly darker color in the upper-right corner of the figure, provides evidence, if anything, of a weak positive sorting between workers and markets. To understand this result better, it is useful to think about what lies behind the market fixed effect. As mentioned, the deciles are computed over the average of market effects across years; thus, the correlation does not stem from lower-wage workers accessing the market during the positive turn of the cycle in the later years of the sample. Instead, the correlation between worker and market effects must be driven by place or occupation. Workers may initially be in low-wage occupations/places and move up the job ladder to better opportunities. In other cases, they may simply move horizontally or even slip down the job ladder. Thus, it is not clear that the correlation between worker and market effects should always be positive. To provide further illustration, Figure 5 shows the market-year fixed effects over the twelve-year period in the sample, by decile of worker fixed effects. Low-wage workers (circle-dotted blue line) initially sort into better-paying markets than their counterparts. This fact is, however, reversed after eight years in the sample, where high-fixed effects workers surpass low-fixed effects ones. This shows that higher-wage workers tend to be in markets that grow faster or move to markets that have higher premia. These are all characteristics of occupations usually associated with higher skills and wages, such as managerial positions and skilled and technical professions (see Figures 2 and 10). Thus, it is possible to conclude that there is a positive sorting between workers and markets, especially after we consider the impact of market effects drift and job-ladder upgrading.

5.3. The impact of other employers' pay policies on wages

Leave-out average firm effects The other object of interest from equation (4) is $\gamma\overline{\zeta}_{-fmt}$, which measures the impact of changes in the pay policies of other employers in the same market on worker *i*'s wages. The purpose of this object is to capture, in a reduced-form fashion, the effects of standard search and matching mechanisms, such as on-the-job search and wage renegotiation. For this to be true, the leave-out average of firm effects, $\overline{\zeta}_{-fmt}$, should be a good approximation of potential job offers that the worker could get or of what she could earn should she decide to switch jobs within her labor market.

To illustrate how predictive $\overline{\hat{\zeta}}_{-fmt}$ is of job movers' new firm premia, I regress, for those who switch firms within the same market, the new firm premia on the estimated $\overline{\hat{\zeta}}_{-fg,t-1}$. Figure 6 illustrates these regressions in a scatter plot, showing a regression slope of 0.78, unveiling a close relationship between the leave-out (weighted) average of firm premia in the market and the premia of destination firms for job switchers. Translating

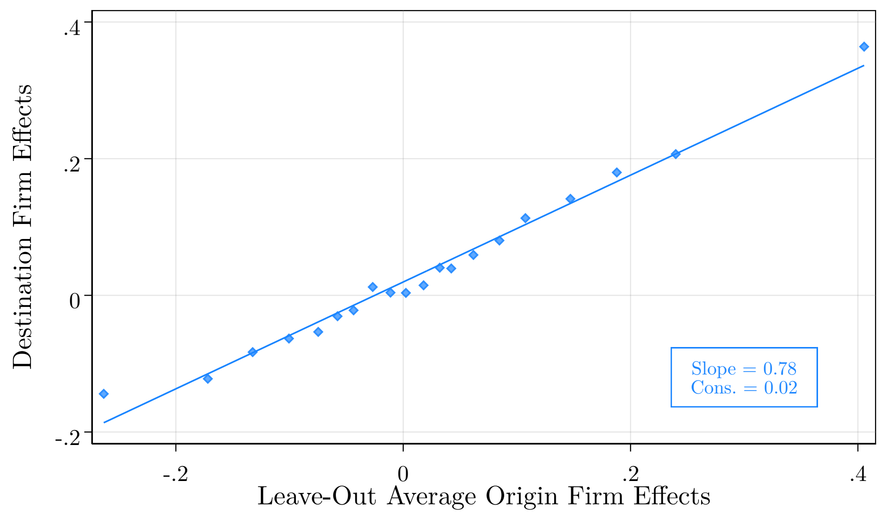


FIGURE 6. Firm effects for job movers and leave-out weighted average

this to a correlation coefficient yields a value of 0.52. This relationship is also positive, yet less strong if instead of considering only movers within the same market I also include those who move across markets (see Figure 9). This positive correlation shows that the average firm premia of alternative firms in a market is a good predictor of what workers get once they switch firms. Note that this formulation implicitly assumes that search is partially random and that all firms in a market have a positive probability of being reached. With better data, one could refine this process and focus, instead, on firms that are actually hiring workers or, even better, on firms for which each worker would like to move to. Nonetheless, the current setup can be grounded in theory, as models such as those in Beaudry, Green, and Sand (2012) and Tschopp (2017) show that, with market-level matching functions, the probability of a worker meeting a vacancy from a particular job is proportional to that job's employment share in the market.

Table 2 presents the mean, median and skewness of the estimated $\bar{\hat{\zeta}}_{-fmt}$ for the full sample as well as different groups of workers. To construct the table, I subtracted, for each worker, the estimated firm fixed effect ($\hat{\zeta}_f$) from the estimated leave-out average of firm effects $\bar{\hat{\zeta}}_{-fmt}$, obtaining, therefore, an assessment of the difference that the worker would get should they move to the average firm in their market (except their own). The table shows that, for the average and median worker, other firms in their market pay premia that are 0.01 log points lower than their current firm's, on average. Thus, should workers find and accept random jobs within their market, they would be worse off in terms of pay. Obviously, this does not imply that job-to-job moves are bad – in fact, the evidence shows that movers tend to upgrade their positions (see Figure 11); instead, this can be rationalized by: 1) workers searching randomly but tending to accept jobs that offer a higher premia; 2) workers searching in a directed manner; 3) firms who actually post vacancies being those with higher premia, on average. None of these three features invalidates the estimated model. First, being a reduced-form model, it captures equilibrium states, i.e., after search and bargaining has resolved. Thus, the data are simply telling that, after searching and bargaining over their contract, workers end up in firms that pay a higher premium than the average of potential counterparts. Second, the fact that the average premia of alternative firms are lower does not imply that workers do not use their offers for bargaining purposes. From a theoretical standpoint, workers and firms bargain over *surpluses*. Thus, receiving an offer from a firm with a lower wage premium but better amenities may mean that the vacancy offers a higher surplus to the worker – which can then be used for bargaining purposes. Hence, having an expected lower wage premium from alternative job offers is not an indication that workers will not bargain over them.

When looking at the differences across groups, the general conclusion is that groups with characteristics usually associated with higher wages also have a bigger (negative) gap between the leave-out average of firm effects and their own firms' premia. This is true for workers with a college degree vs. non-college workers, male vs. female and workers uncovered by a CBA vs. covered ones. This is also seen when splitting workers into wage quantiles. At the bottom, we see that other firms pay, on average, 0.07 log points better wages than the current firm; as we move along the distribution, this difference turns negative and larger, reaching -0.13 log points for workers in the top decile. In general, workers at the top of the wage distribution have better job matches, which is also reflected in the positive sorting unveiled in Figure 4 and discussed in the previous section. Thus, because of this, their alternative job options may be (on average) of lower quality than those of workers at the bottom of the wage distribution. Lastly, when splitting the sample between low and high labor market concentration – defined as an HHI below or above the median –, the results show that those in more concentrated markets have a lower average quality of alternative options relative to their current employer than their counterparts in less concentrated markets. In low concentration markets, the difference between current and other firm effects is close to zero, whereas it goes down to -0.02 log points in high HHI markets. This may stem from the fact that less concentrated markets also have fewer large firms, which, on average, are higher-paying, implying a lower within-market variation in pay policies. On the flip side, high concentration markets are dominated by larger firms, and, for workers in these firms, job alternatives are of lesser quality. This is in line with the model postulated in Jarosch, Nimczik, and Sorkin (2024), where workers in more concentrated markets have worse truly outside options (i.e., job alternatives outside of their own firm).

The elasticity of wages to alternative firms' pay policies How do changes in the quality of other firms' pay policies affect a worker's wage? Theoretically, the answer to this question

TABLE 2. Summary statistics of leave-out average firm effects, by group

	Mean	Median	Skewness
Full sample	-0.0132	-0.0093	-0.1554
Education			
No college	-0.0088	-0.0052	-0.1112
College	-0.0297	-0.0233	-0.2791
Gender			
Female	-0.0056	-0.0037	-0.1498
Male	-0.0198	-0.0160	-0.1232
CBA Coverage			
No CBA	-0.0176	-0.0146	-0.4363
CBA	-0.0126	-0.0082	-0.1151
Wage quantiles			
< P25	0.0707	0.0503	0.7444
P25 to P50	0.0072	-0.0001	0.3775
P50 to P90	-0.0487	-0.0396	-0.1536
> P90	-0.1323	-0.0860	-0.8340
HHI			
Low concentration	-0.0037	0.0003	-0.1262
High concentration	-0.0228	-0.0158	-0.2729

Notes: Leave-out average of firm effects within market, weighted by employment. The average represents the deviation in log points relative to workers' current firm effect. Low concentration = HHI index within market-year lower than the median. Wage quantiles defined within year.

is not straightforward. Models of industrial composition, such as Beaudry, Green, and Sand (2012) and Tschopp (2017) show that the wages of workers in a given industry and city are positively correlated with the wages of all other industries. Hence, these models would predict a positive elasticity of wages to alternative firms' pay policies, i.e., $\gamma > 0$. Because the SBM can cluster firms from different industries into the same market, this mechanism could very well be captured by γ in my model.

The search and matching models with wage renegotiation and bargaining, as pioneered by Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006) show different possible predictions. As mentioned in Section 2, in these models, because workers can search on the job and obtain more favorable offers, firms can initially pay lower wages to back-load future possible increases from renegotiation, provided that they have some bargaining power. This "quit/renegotiation" term would predict that wages are decreasing

TABLE 3. Theoretical predictions for γ

Mechanism	Source	Prediction
Industrial composition effects	Beaudry, Green, and Sand (2012) Tschopp (2017)	$\gamma > 0$
Outside options	Cahuc, Postel-Vinay, and Robin (2006) Caldwell and Danieli (2024) Berger et al. (2024)	$\gamma > 0$
Quit/Renegotiation	Postel-Vinay and Robin (2002) Cahuc, Postel-Vinay, and Robin (2006) Bagger et al. (2014) Berger et al. (2024)	$\gamma < 0$
Information channel	Caldwell and Harmon (2019)	$\gamma > 0$

in other firms' pay policies, i.e., $\gamma < 0$. This can also be seen as a compensating differential (Lamadon et al. 2024), as workers are (negatively) compensated for future increases in their position. However, bargaining models also show that workers receive a share of their outside option, be it measured as the lost value of unemployment (Berger et al. 2024) or as their next best offer Caldwell and Danieli (2024). In this case, positive changes in the quality of other firms' policies through the structure of the market impact workers' outside options, driving up wages. These two mechanisms counteract each other and the net effect on wages is ambiguous. Lastly, the leave-out average of firm effects may also reflect changes in the probability of receiving better outside offers due to improved information about the market. By having better knowledge about potential outside offers, workers ameliorate their search and may, therefore, have a higher probability of receiving a good offer (Jäger et al. 2024). This mechanism, recently explored in Caldwell and Harmon (2019), would predict that $\gamma > 0$. All in all, it is unclear what direction γ should take. Table 3 provides a summary of these predictions.

Table 4 presents the results of estimating the models in equations (3) and (4). Annex Table 16 presents all the estimated coefficients. The first two columns show the results without the market-year fixed effects. The table presents bias-adjusted coefficients in columns 2 and 4 as discussed in section 4.3.5, which are the main coefficients of interest. It shows that, after bias correction, a 10% increase in the quality of alternative firms is associated with an increase in wages, on average, of about 2.8%. This elasticity lies slightly above the estimates of 1% in Schubert, Stansbury, and Taska (2024) and 1.7% in Caldwell and Danieli (2024), but below the larger effect of 7% found in Tschopp (2017). However, the inclusion of the market-year fixed effect flips the sign, with the elasticity dropping to -0.1. These effects are statistically significant at any reasonable significance level, with standard errors clustered at the firm-year level.[3] Another intuitive way to think about the magnitude of these coefficients is to interpret them based on the variation of firm effects quality within markets. To do so, I calculate the standard deviation of the leave-out estimated firm effects for each market-year pair, and then average them across the sample. To this standard deviation, I then multiply by the respective coefficient to obtain an interpretation of γ in terms of this variation. A one standard deviation increase in the quality of outside options adjusts wages by 3.62% in the case without market-year effects and -1.25% in the full model, after bias adjustments.

To understand these findings, consider the wage equation presented in Section 2. As mentioned, standard search arguments state that, with Nash bargaining, the worker should get a share of the unemployment value, which is a function of b and $\sum_{f \in m} \lambda_f S_f$. Changes in either the structure of pay policies or the employment shares of firms in this market would, therefore, affect $\sum_{f \in m} \lambda_f S_f$. In my statistical model, however, all the of variation that happens simultaneously for all firms in a market is absorbed by the market-year fixed effect. In other words, including this fixed effect averages out this outside option term, which is then not captured in $\gamma \bar{\zeta}_{-fmg}$. Therefore, what is left after the inclusion of the market-year fixed effect are idiosyncratic changes in the structure/quality of the market. Another way to think about this is that in the absence of match-specific amenities or shocks that make the value of working at firm f specific to each individual, then the unemployment value term is common across all workers in a market. Thus, the inclusion of the market-year fixed effect washes away this mechanism. On the flip side, in the presence of match-specific amenities or worker-firm-specific finding rates, the inclusion of this fixed effect does not capture the full impact of the outside option channel, since each worker has a different value from being employed in each firm, even conditional on type.

These findings highlight that the outside options term has a stronger impact on wages than the wage backloading mechanism, implying that, on average, positive changes in the value of alternative offers lead to wage increases. This vindicates the findings in Berger et al. (2024), who show that, in Norway, the share of total wages explained by the outside options channel is 42%, whereas the quit/promotion discount is only of -14.6%.

5.4. The Quit/Renegotiation Mechanism

The negative elasticity presented in Table 4 is unsurprising considering the structure of the model. Recalling the possible mechanisms at play, changes in the quality of other firms' pay policies influence both the outside option value of work (worker bargaining yields a

[3] Clustering the standard errors at the worker or firm-level does not change the statistical significance of the result.

TABLE 4. Elasticity of wages to other firms' pay premia

	(1)	(2)	(3)	(4)
$\hat{\gamma}$	0.2117***	0.2784***	-0.0731***	-0.1002***
	(0.0038)	(0.0073)	(0.0045)	(0.0063)
Worker FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Market-Year FE	–	–	✓	✓
Split-Sample?	–	✓	–	✓
Weighted?	✓	✓	✓	✓
Observations	16,064,983	16,064,983	16,064,983	16,064,983

Note: Controls for age squared, education and a quadratic function of tenure. Standard errors clustered at firm × year level. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares.
*** Denotes statistical significance at the 0.01 level.

share of the outside option to the worker) and the potential future wage raises through on-the-job-search (workers renegotiate based on outside offers, which should yield future wage growth). There are, however, other possible mechanisms at play. Recently, Paula et al. (2025) show that wages can also be depressed due to the difference in human capital and information acquisition between a worker's chosen firm and their second-best option. While this can also be a factor influencing future renegotiations and quits, the underlying mechanisms slightly differ from the more standard theoretical models.

Nonetheless, to further convince the reader that $\hat{\gamma}$ is capturing the quit/promotion channel in Table 4, I perform two extra exercises. First, the effect of other firms' pay premia on wages should be stronger for workers whose promotions are further in the future (Cahuc, Postel-Vinay, and Robin 2006). To explore this, I estimate the following model:

$$\begin{aligned} w_{ifmt} = \boldsymbol{\beta}\mathbf{x}_{ifmt} + \alpha_i + \theta_{mt} + \zeta_f + \mathbb{1}\left[\text{New Hire} = 1\right] + \\ + \overline{\zeta}_{-fmt}\left(\gamma_0 + \gamma_1 \cdot \mathbb{1}\left[\text{New Hire} = 1\right]\right) + \varepsilon_{ifmt} \end{aligned} \tag{20}$$

where New Hire = 1 if the worker's tenure with the firm is weakly less than 12 months. With this specification, one can test whether $|\gamma_1| > 0$, i.e., whether the elasticity is larger for new hires, as predicted by theory.[4]

Table 5 shows the results from estimating (20) with the NLS approach. As anticipated,

[4]The estimation of (20) is computationally more demanding given the extra non-linearity introduced with the indicator function. Future versions of the paper will include a split-sample bias adjustment, which, for now, is not displayed.

TABLE 5. Elasticity of wages to other firms' pay premia, by new hire status

	(1)
$\hat{\gamma}$	-0.1550***
	(0.0165)
$\hat{\gamma}$ × New hire = 1	-0.0508***
	(0.0141)
Worker FE	✓
Firm FE	✓
Market-Year FE	✓
Split-Sample?	✓
Weighted?	✓
Observations	14,401,150

Note: Regression estimated with a new hire indicator interacted with $\overline{\zeta}_{-fmt}$. New hire = 1 if the worker has less than 12 months of tenure with the firm. Controls for age squared, education and a new hire indicator. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares.
** Denotes statistical significance at the 0.05 level.
*** Denotes statistical significance at the 0.01 level.

the effect of the leave-out average of firm effects is stronger for newly hired workers – twice as strong, in fact. Note that the outside options channel could also predict that $\gamma_1 > \gamma_0$ due to the effect of information – newly hired workers, by being fresh off the job market, have a better understanding of potential alternative offers, thus having either larger bargaining power or an increased chance of better offers in the future (Caldwell and Harmon 2019; Jäger et al. 2024).

The second exercise is related to non-wage outcomes that could be linked to changes in market structure. More specifically, I estimate how the average quality of other firms in the market is related to promotions and job separations. The literature finds that a higher chance of having a better-paid job outside the current one increases the chance of future wage rises through renegotiation or job-to-job moves. This higher chance can be driven by either a higher job offer arrival rate or an improvement in the quality of outside offers, which, in my model, is proxied by the leave-out weighted average term. In Quadros de Pessoal, it is not possible to observe wage renegotiations or the reason for a job separation. I proxy the former with an indicator variable that equals one if the worker has been promoted over the past year (information available in QP), while the latter is an indicator that equals one if a worker's firm at t is different from the one at $t-1$. With this, I estimate:

$$y_{ifmt} = \boldsymbol{\beta}\mathbf{x}_{ifm} + \delta\bar{\hat{\zeta}}_{-fm,t-1} + \text{centrality}_i + \varepsilon_{ifmt} \tag{21}$$

where $y_{ifmt} = \{\text{Promotion, Separation}\}$, being equal to one if the worker has been promoted or separated to a different firm over the past year.; $\mathbf{x}_{ifm}$ includes age, age squared, a gender indicator, education and tenure; $\bar{\hat{\zeta}}_{-fm,t-1}$ is the leave-out weighted average of firm effects in worker i's market in $t-1$; centrality_i is an eigen-vector centrality measure, aimed at capturing the fact that more central workers tend to move between jobs more often; and ε_{ifmt} captures the error term. The coefficient of interest is δ, which should capture the quasi-elasticity of the outcome variable to changes in the estimated leave-out average of firm effects. Given the relatively low prevalence of separations in the dataset, I estimate equation (21) as a linear probability model as well as a complementary log-log (cloglog) model. The latter also has the added benefit of mapping to a discrete time hazard model with proportional hazards. To overcome the bias due to the generated regressor, I adjust the estimated δ using the split-sample jackknife approach of Dhaene and Jochmans (2015) described in section 4.3.5.

The strategy of using a two-step approach to estimate the elasticity of separations to firm pay premia is not new, being first introduced in Bassier, Dube, and Naidu (2022). In it, the authors first estimate the AKM firm pay premia and then use these in a regression akin to (21). This is not, however, a fully satisfying method, as also discussed in Bassier, Dube, and Naidu (2022), as it is plagued by composition biases. Just as we find, in AKM, that some workers are "high-wage workers", it may also be true that some workers are "high-separation" workers, i.e., workers whose probability of moving to other firms is larger. This can be true because they are better connected in the job market network, because they wish to progress faster along the job ladder, or because they slip often from its rungs. To alleviate some of these issues, I control for a worker's eigenvector centrality, a measure of network centrality based not just on how many peers one worker has throughout their work history, but also how many peers her peers have. Furthermore, I also include as controls the worker, firm and market-year wage fixed effects estimated from equation (4). The inclusion of these fixed effects as controls is not without controversy, as it may be attenuating the composition bias while, at the same time, aggravating the generated regressor bias.

Table 6 shows the estimates for the separations elasticity. All versions show a positive relationship between the average quality of other firms in the market and the probability of joining another firm in the future. When translated to an elasticity, the cloglog base model shows that a 10% increase in the average outside firm quality in the market is associated with a 4% increased probability of moving to another job. The results are not very sensitive to the modeling choice, ranging from 0.4 to 0.5 in the cloglog model with all

TABLE 6. Elasticity of separations to outside options

	(1) LPM	(2) LPM	(3) LPM	(4) Cloglog	(5) Cloglog	(6) Cloglog
$\hat{\delta}_{\text{Separations}}$	0.0269^{***}	0.0249^{***}	0.0283^{***}	0.0255^{***}	0.0253^{***}	0.0301^{***}
	(0.0038)	(0.0034)	(0.0033)	(0.0036)	(0.0031)	(0.0031)
Elasticity	0.4337	0.4024	0.4566	0.4115	0.4077	0.4857
Centrality	✓	✓	✓	✓	✓	✓
Worker Wage FE	–	✓	✓	–	✓	✓
Firm Wage FE	–	✓	✓	–	✓	✓
Market-Year Wage FE	–	–	✓	–	–	✓
Split-Sample?	✓	✓	✓	✓	✓	✓
Weighted?	✓	✓	✓	✓	✓	✓
Observations	15,664,813	15,664,813	15,664,813	15,664,813	15,664,813	15,664,813

Note: The dependent variable is a binary variable which equals 1 if the worker is in another firm in the next year. Controls for age and its square, education, tenure and a male dummy. The wage fixed effects are obtained form the estimation of equation (4). The elasticities are obtained by dividing the coefficients on $\overline{\zeta}_{-fmt}$ by the average separation rate in the sample. Split-sample refers to generated regressor adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level.
*** Denotes statistical significance at the 0.01 level.

wage fixed effects included as controls.

This result corroborates similar findings in the literature. Caldwell and Harmon (2019) shows that a standard deviation increase in her outside options measure leads to a 15% increased chance of moving to another job. Jäger et al. (2024) show that, once workers are better informed about their possible outside options, they tend to correctly update their beliefs and adjust job search accordingly. While the authors do not have data on actual job moves, these two factors should contribute to increased mobility. Furthermore, the fact that the elasticity is not too large also goes in line with recent research (Caldwell, Haegele, and Heining 2025) which shows that workers are reluctant to change employers despite having better outside options because switching costs are large.

When it comes to promotions, the estimated elasticities are higher. Table 7 shows that a 1% increase in the leave-out average of firm effects is associated with a 1.5% increase in the chance of being promoted next year, although the estimates are much wider across specifications. Including worker and firm wage fixed effects as controls attenuates the elasticity, dropping to 0.8. Regardless, the positive association is present for both outcomes. This is an indication that the current structure of firm premia in a given market is positively correlated with future promotions or job-to-job separations. This effect corroborates the idea that firms may mark down wages at hiring and early tenures because they anticipate

TABLE 7. Elasticity of promotions to outside options

	(1) LPM	(2) LPM	(3) LPM	(4) Cloglog	(5) Cloglog	(6) Cloglog
$\hat{\delta}_{\text{Promotions}}$	0.0367***	0.0181***	0.0258***	0.0378***	0.0188***	0.0238***
	(0.0057)	(0.0042)	(0.0042)	(0.0055)	(0.0042)	(0.0041)
Elasticity	1.4949	0.7368	1.0502	1.5416	0.7650	0.9681
Centrality	✓	✓	✓	✓	✓	✓
Worker Wage FE	–	✓	✓	–	✓	✓
Firm Wage FE	–	✓	✓	–	✓	✓
Market-Year Wage FE	–	–	✓	–	–	✓
Split-Sample?	✓	✓	✓	✓	✓	✓
Weighted?	✓	✓	✓	✓	✓	✓
Observations	15,664,813	15,664,813	15,664,813	15,664,813	15,664,813	15,664,813

Note: The dependent variable is a binary variable which equals 1 if the worker is promoted over the following year. Controls for age and its square, education, tenure and a male dummy. The wage fixed effects are obtained form the estimation of equation (4). The elasticities are obtained by dividing the coefficients on $\overline{\zeta}_{-fmt}$ by the average promotion share in the sample. Split-sample refers to generated regressor adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level.
*** Denotes statistical significance at the 0.01 level.

steeper wage schedules in the future.

5.5. Robustness

Alternative definitions of peer groups The estimation of the elasticity of wages to the quality of alternative firms hinges on the assumption that the average of other firm effects is computed with the correct firms, i.e., that the peer group is well defined. The peer group is characterized by the intersection between the markets obtained from the clustering algorithm of the SBM in section 4.1 and occupation, with the assumption being that workers tend to search for jobs in similar occupations. However, this assumption could be dropped and, instead, I could define the peer group solely from the groups obtained from the SBM. This is what is shown in the first column of Table 8. Using only the SBM blocks to define the peer group yields an elasticity of -0.27, larger (in absolute value) than the one obtained in the previous exercise. This is not surprising, as this definition of the peer group considers a better set of alternative options, and thus, wages react more strongly.

Another alternative is to ditch the SBM altogether and use a simpler definition of the labor market. Column 2 of Table 8 considers that markets are defined as those workers in the same occupation, location (given by NUTS II) and year. For example, this considers all

TABLE 8. Elasticity of wages to other firms' pay premia, alternative peer groups

	Peer group definition	
	SBM only	Occ. × Location × Year
	(1)	(2)
$\hat{\gamma}$	-0.2692***	-0.1263***
	(0.0491)	(0.0169)
Worker FE	✓	✓
Firm FE	✓	✓
Market-Year FE	✓	✓
Split-Sample?	–	–
Weighted?	✓	✓
Observations	16,064,983	16,064,983

Note: Column 1 shows the result from estimating model (4) with peer group defined solely from the SBM, i.e., without restricting to occupation. In column 2, peer groups are defined as individuals in the same occupation, NUTS II and year. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level.
*** Denotes statistical significance at the 0.01 level.

mechanical engineers in the Lisbon region to be in the same labor market and, therefore, search for opportunities in any firm that has at least one person performing that job in the region, in a given year. This yields an elasticity of -0.13, very close to the one found in the main exercise. This hints at the fact that occupation is the strongest source of variation in the definition of peer groups in the previous section. Both results also imply that the application of the SMB for community detection does not yield spurious results, and that the elasticities from Table 4 are credible.

Quality of outside firms as unweighted average Table 9 compares the results from estimating $\hat{\zeta}_{-fmt}$ as an unweighted average of firm effects against the weighted average used throughout the paper. The first two columns show the results for the unweighted average of leave-out firm effects. The first column displays the estimated value of γ without adjusting for the bias induced by the non-linearity of the model. In this case, a 10% increase in the average quality of firms in that market would be associated with a 0.2% increase in wages, on average, whereas the bias-corrected estimate in column 2 shows a null effect. If, instead, I consider $\hat{\zeta}_{-fmt}$ as the average of firm effects weighted by employment, the results change considerably. Columns 3 and 4 show that the elasticity of wages with respect to alternative firm policies lies between -0.07 and -0.1. In other words, a 10% increase in the quality of alternative firms' pay policies is associated with a decrease in wages ranging from -0.7 to -1%.

The differences between the unweighted and weighted coefficients stem from the variation used in identifying each parameter. By relying on firms exiting and entering a labor market, the variation in the leave-out firm effects resembles the idea that outside options change because of enlargements or reductions in the set of available alternative firms, much akin to the definition of outside options in Caldwell and Danieli (2024). This then leads to an estimated γ that is consistent with the theory – the entry of a high-quality firm in one's available choice set has a positive effect on wages through a bargaining channel. This source of variation is, however, problematic and noisy. The power of the identifying variation relies, first of all, on a lot of firms entering or exiting markets in each year, and second, on small "peer group" sizes (i.e., market-occupation-year cells with a small number of firms). Borrowing from the IV terminology, the first stage is weak if any of these conditions fail. Starting with the peer group size, the median and average sizes are, respectively, 3 and 6, which is a good size for proper identifying variation. However, 64% of the markets see no change in the composition of firms each year. This is a sort of limited mobility bias that does not allow for a precise estimation of $\hat{\gamma}$, and it is why the second column shows a bias-adjusted coefficient of zero.

The weighted average version of the model relies on variation in the employment of firms within a market. This is better aligned with models of industrial composition that link the number of vacancies to the employment share of each firm in the market (Beaudry, Green, and Sand 2012). In this case, when a high-quality firm in the market expands its market share, all other workers in other firms have a better chance of being contacted by this firm in the future. This variation is also stronger, as it relies on firms expanding/reducing their labor force, so hiring and firing/quitting by continuing firms play a major role in identifying γ. Furthermore, Caldwell, Haegele, and Heining (2025) show that workers have relatively accurate beliefs about pay in large employers. Thus, having an average that assigns bigger weights to larger employers mitigates issues that may stem from inaccurate beliefs about market pay.

5.6. Heterogeneity

This section dissects the heterogeneity of the elasticity of wages to the leave-out average quality of firm pay across several dimensions: education, occupation groups, industries and level of labor market concentration. The first two can be seen as an exploration of the skill dimension. More educated workers and those in more cognitive-intensive occupations are, in the economics literature, usually referred to as high-skilled workers. While the inherent ability of the worker is averaged out in equation (4) due to the worker fixed effect, there is still value in assessing the differences across groups, as there may be elements of the market pay structure that interact with skill in a non-additive, time-varying manner (Bagger et al. 2014; Paula et al. 2025). Moreover, there is also recent evidence show-

TABLE 9. Elasticity of wages to other firms' pay premia – Unweighted vs. weighted average

	(1)	(2)	(3)	(4)
$\hat{\gamma}$	0.0249***	0.0078	-0.0731***	-0.1002***
	(0.0047)	(0.0064)	(0.0045)	(0.0063)
Worker FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Market-Year FE	✓	✓	✓	✓
Split-Sample?	–	✓	–	✓
Weighted?	–	–	✓	✓
Observations	16,064,983	16,064,983	16,064,983	16,064,983

Note: Standard errors clustered at firm × year level. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares.
*** Denotes statistical significance at the 0.01 level.

ing that information about wage offers may be quite heterogeneous across occupations (Batra, Michaud, and Mongey 2023), which evidently affects the channels investigated in this paper. The industry dimension is also interesting to investigate, as industries may vary in terms of pay transparency and mobility patterns through collectively bargaining agreements (de Almeida Vilares and Reis 2022) and non-compete agreements (Krueger and Ashenfelter 2022; Johnson, Lavetti, and Lipsitz 2025), both of which may also interact with job search. Lastly, performing a heterogeneity analysis by the level of labor market concentration speaks to recent advances in the monopsony literature, which show a direct link between higher concentration and lower wages through the outside options channel (Berger, Herkenhoff, and Mongey 2022; Jarosch, Nimczik, and Sorkin 2024; Berger et al. 2024).

Education Table 10 shows the coefficients for separate regressions by education level, where low-educated workers are those with at most twelve years of education, corresponding to high school in the Portuguese system. Whereas in the main model, one worker could have in their peer group workers from all education levels (provided that they worked in the same market and occupation), now peer groups are constrained to have workers in the same education group (within-group they may still have distinct years of schooling). The results show that only low-educated workers are affected by changes in the average quality of competitor firms in the market, after accounting for market-year fixed effects. For the less educated, a 10% increase in the average quality of competitors is associated with 1.3% lower wages, whereas for higher education workers, the results are indistinguishible from zero. This can be driven by several factors. First, more educated workers may have a

TABLE 10. Elasticity of wages to other firms' pay premia, by education group

	Low education		High education	
$\hat{\gamma}$	-0.1026***	-0.1338***	-0.0023	0.0002
	(0.0048)	(0.0069)	(0.0077)	(0.0122)
Worker FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Market-Year FE	✓	✓	✓	✓
Split-Sample?	–	✓	–	✓
Weighted?	✓	✓	✓	✓
Observations	12,327,715	12,327,715	2,949,699	2,949,699

Note: Separate regressions for low and high education workers. Low education refers to workers that have a level lower than or equal to high school. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level.
*** Denotes statistical significance at the 0.01 level.

higher bargaining power, therefore receiving a larger share of the match surplus. If this is true, then these workers are paid a wage that is closer to their marginal product, and firms are not able to mark down wages, rendering the wage backloading channel irrelevant for these workers. Another possible explanation hinges on the possibility that the wage ladder is steeper for low educated workers, thus leading to a higher wage markdown that insures against future raises.

Occupation Table 11 shows the results from estimating the model separately by occupation group. It shows that the elasticity of wages to the average quality of alternative firms is larger (more negative) for occupation groups that usually require less education and in which the type of work is more commonly routine or manual-intensive, such as sales, craft trades and elementary occupations. The elasticities reach up to -0.4 in craft and elementary occupations. Conversely, skilled and technical professionals have lower elasticities, ranging from -0.04 to -0.08. The estimate for managerial professionals is large but imprecise, being statistically indistinguishable from zero.

These results are in line with some of the literature on bargaining power estimation. In their seminal work, Cahuc, Postel-Vinay, and Robin (2006) estimate a larger bargaining power for more skilled occupations, even reaching the conclusion that, for the less skilled, the workers' share of the match surplus can be zero. From their model, such a result implies a strong effect from the quit/renegotiation channel. de Almeida Vilares and Reis (2022) estimate trends in bargaining power for different groups of workers based on their job title within collectively bargained agreements, in Portugal. The authors show that managers have a large degree of bargaining power, whereas skilled and unskilled workers have similar levels. As with education, the mechanism behind the heterogeneous elasticities is unclear, but it is highly likely to be a combination of different bargaining power levels and wage profiles.

Industry The results by industry in Table 12 showcase the common trends aforementioned: industries with a higher share of educated, high-skilled professionals have weaker elasticities. In manufacturing, trade and transportation, where more than 50% of the sample lies, the elasticities range from -0.04 to -0.07, reasonably in line with aggregate results. The biggest outlier is the construction industry, with a coefficient of -0.27, which, considering the composition of its workers, is in line with the previous results on education and occupation heterogeneity.

Labor market concentration Lastly, Table 13 presents the estimation results by level of labor market concentration. A low concentration market is one where the market-level HHI is below the national median, computed yearly. In line with recent research relating labor market power to monopsony power, the results claim that more concentrated markets have a lower elasticity of wages to other firms' pay policies. This relates to the notion that in highly concentrated markets the outside options truly outside of a firm are much fewer, implying lower competition for workers and thus granting firms a level of monopsony power over workers (Jarosch, Nimczik, and Sorkin 2024). Thus, the quit/renegotiation channel is much weaker in more concentrated markets because the chances of getting better offers are much lower (Berger et al. 2024).

6. The impact of market pay structure on inequality

The study of the role of worker and firm unobserved heterogeneity in affecting wage inequality has developed substantially since the seminal work of Abowd, Kramarz, and Margolis (1999). By now, it is widely accepted that, after adjusting for limited mobility, high-wage workers work for high-wage firms. In fixed effects terms, this means that workers with high values of α_i tend to work for firms with high values of ζ_f. Recent developments have tried to reconcile the statistical model of AKM with the wage-setting literature, bridging the gap between empirics and theory, trying to untangle why, in some cases, this worker-firm sorting is not as strong as a standard bargaining model could predict. Researchers have pointed to the role of occupation heterogeneity (Torres et al. 2018), the effect of previous firms' policies (Di Addario et al. 2023), learning about type (Paula et al. 2025), and even other forms of sorting (Lentz, Piyapromdee, and Robin 2023). This section investigates the role that market structure may have in shaping the wage distribution and how it can change the knowledge on wage sorting.

To perform this exercise, I do an AKM-style variance decomposition of log wages, where the variance of wages is decomposed into the contributions of worker, firm, market

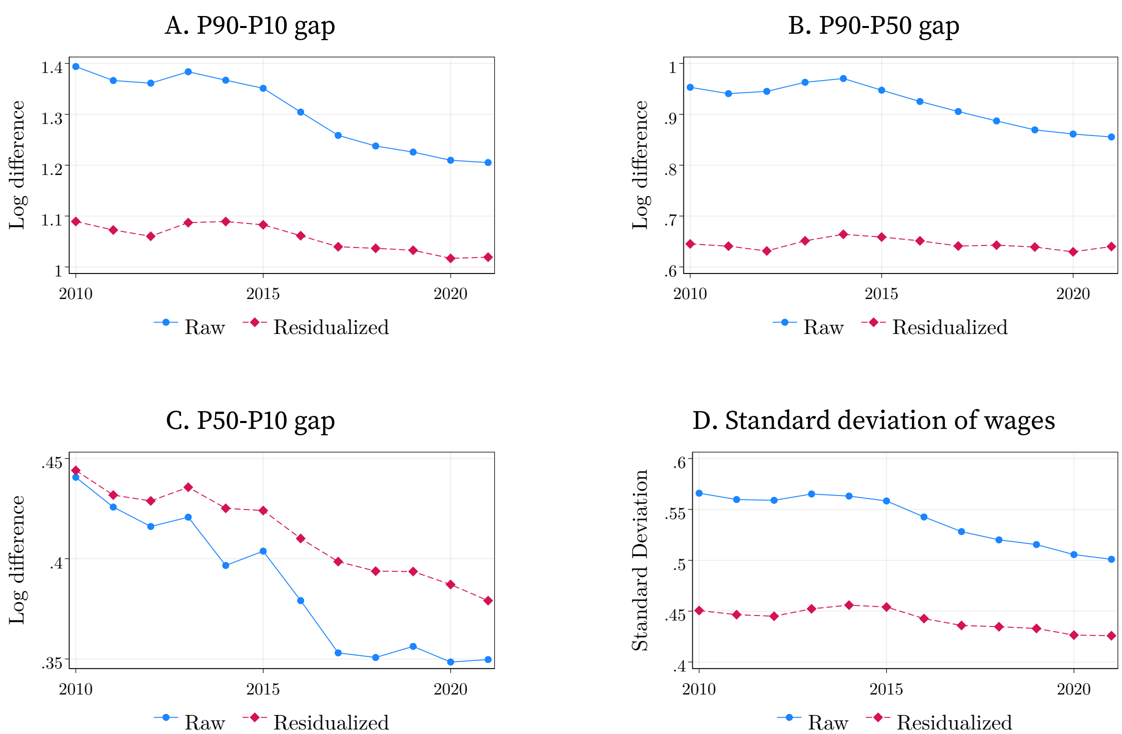


FIGURE 7. Measures of wage inequality, 2010-2021

Note: Log real hourly wages residualized according to a Mincer equation controlling for quadratic terms in age and tenure and education estimated for each year.

structure and other time-varying controls:

(22)

$$
\begin{aligned}
\mathbb{V}\left[w_{ifmt}\right] &= \mathbb{V}\left[\boldsymbol{\beta}\mathbf{x}_{ifmt} + \alpha_i + \theta_{mt} + \zeta_f + \gamma\bar{\zeta}_{-fmt} + \varepsilon_{ifmt}\right] \\
&= \mathbb{C}\left[\boldsymbol{\beta}\mathbf{x}_{ifmt}, w_{ifmt}\right] && \text{Contr. of covariates} \\
&+ \mathbb{C}\left[\alpha_i, w_{ifmt}\right] && \text{Contr. of worker effects} \\
&+ \mathbb{C}\left[\theta_{mt}, w_{ifmt}\right] && \text{Contr. of market-year effects} \\
&+ \mathbb{C}\left[\zeta_f, w_{ifmt}\right] && \text{Contr. of firm effects} \\
&+ \mathbb{C}\left[\gamma\bar{\zeta}_{-fmt}, w_{ifmt}\right] && \text{Contr. of leave-out firm effects} \\
&+ \mathbb{C}\left[\varepsilon_{ifmt}, w_{ifmt}\right] && \text{Contr. of residual}
\end{aligned}
$$

where $\mathbb{C}\left[\cdot, w_{ifmt}\right]$ represents the covariance between each element and the log of real hourly wages. This is a high-level decomposition that does not provide any information on the covariances between fixed effects. I start with this version of the variance decomposition for exposition purposes and, in a second exercise, delve deeper into the covariance structure of the fixed effects.

For context, wage inequality in Portugal is pervasive but has been decreasing throughout the last decade. Figure 7 shows several measures of income inequality, including percentile gaps and the standard deviation of wages. It can be seen that wage variance is still positive even after controlling for age, tenure, education and time, which suggests the need to account for unobserved factors such as ability, firm pay and market structure.

Figure 8 shows the wage variance decomposition proposed above for two models. For a more detailed version, see Table 17. The first is the standard two-way fixed effects model as in Abowd, Kramarz, and Margolis (1999), i.e. accounting for worker and firm time-invariant unobserved heterogeneity (denoted "Two Fixed Effects", TFE henceforth); the second is the model starring in this paper that adds market-year effects and the impact of other firms' quality on wages, as proxied by the leave-out average of firm effects (denoted "Full Model"). In the TFE model, the contribution of worker characteristics to wage variance is close to 60%, whereas firms contribute with 26%. The remainder is split between covariates and unexplained factors. The contribution of worker heterogeneity to the variance is larger than that found in Torres et al. (2018) for Portugal, albeit using a different time period. When accounting for market structure effects, the component of the variance explained by workers is dampened to 52% and that of firms to 23%. These differences are compensated for the contribution of the market-year fixed effects, which explain close to 15% of the wage variance. The impact of the average quality of other firms in the market is quite low, at -1.1%, indicating that inequality should, in fact, be slightly higher if all workers had similar outside opportunities. This comparison provides evidence

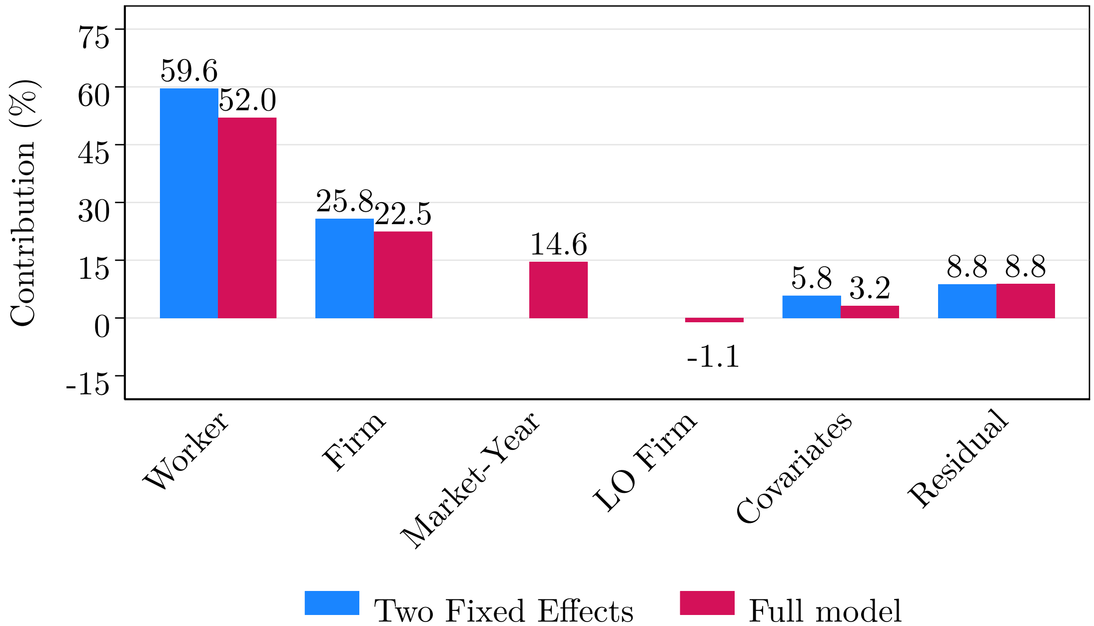


FIGURE 8. Share of wage variance explained by each component

Note: The contribution of each component is calculated according to (22). The worker fixed effects are adjusted for the linear effect of age and gender by residualizing $\hat{\alpha}_i$ on gender and year of birth dummies.

that labor market conditions that are common across all workers are quite important in explaining the variation of wages in Portugal, whereas the markdown associated with the average of outside firm quality is quite irrelevant. The market-year effects are an amalgamation of place, occupation, competition and the effects of local shocks. Without further assumptions, it is not possible to disentangle the impact of each source on wage variation, but it is possible to suppose that, since the largest share of the variation in market effects stems from occupations and time, these should be the main culprits. In fact, Torres et al. (2018) have shown that job-title heterogeneity is key in explaining wage inequality in Portugal, which could be connected with these findings. The irrelevance of the leave-out average of firm effects goes in line with the conclusions in Di Addario et al. (2023), who show that past firms' pay policies are not an important factor for wage inequality. From specific functional forms of the wage equations in Postel-Vinay and Robin (2002) and Bagger et al. (2014), past firms' pay policies are a proxy for the quit/renegotiation channel discussed throughout this paper, thus being related to the leave-out average of firm effects term. These findings also speak to the results in Berger et al. (2024), who show that the outside options channel has a muted effect on markdowns, wage variation and welfare.

Wage sorting Section 5.2 showed that high-wage workers tend to work for high-wage firms and, to a lesser degree, in high-wage markets. It is also possible to dissect how much of this sorting contributes to the total variance of log wages. Table 14 provides the covariance between fixed effects and their respective contribution to the variance. In the TFE model, the sorting of workers with firms explains 13% of the variance. This tells us that, in a counterfactual world where the sorting between workers and firms was random, inequality should decrease by 13%. This is a powerful, well-known result from the literature, which showcases that there is a strong preference for higher wages among high-ability individuals. The full model results show that this is not the only sorting mechanism that contributes to a larger wage dispersion. The fact that high-wage workers tend to sort into markets that pay more contributes to an increase in wage inequality by almost 9%. Furthermore, it is possible that by ignoring this channel, we are overestimating the importance of worker-firm sorting. This can be explained by the fact that market-based amenities – such as place, industry or occupation – are also quite important for an individual's decision of where to work. Thus, when we observe a move to another firm, we need to account for the fact that the worker may be, in fact, also taking other market-specific variables into her decision. Lastly, as in the previous exercise, the share of variance explained by factors related to alternative firms is low.

Limited mobility bias Wage variance decompositions derived from estimated AKM-type models are subject to limited mobility bias, a form of incidental parameter bias that leads to underestimation of the contribution of the worker-firm sorting component (Bonhomme et al. 2023). Appendix B provides a more detailed analysis of the issue and shows that the aforementioned results are robust to the bias correction methods proposed by Andrews et al. (2008) and Kline, Saggio, and Sølvsten (2020).

7. Conclusion

In this paper, I investigate the role of other firms' pay policies and general market structure in determining wages. Underpinned by classic theoretical results in search models, I propose a reduced-form equation where log wages depend not only on worker, firm and market-year fixed effects, but also on the average of other firms' fixed effects. Drawing from the peer effects literature, I estimate a non-linear high-dimensional fixed effects model that jointly uncovers the distribution of fixed effects and the elasticity of wages to the leave-out average of other firms' fixed effects.

The distribution of market-year fixed effects shows that occupation and place have, in general, a growing positive impact on wages over the past decade. Workers in occupations generally deemed high-skilled, such as managers and skilled professionals, have a larger wage premium than those in less-skilled professions. The differences in wage premia across place and sector are more muted, but still present.

Higher-income workers have, in general, better outside options when compared with those in lower income brackets. However, when compared with their current situation, the situation is reversed: should a high-income worker switch to the average firm in the market, their wages would be expected to be 0.13 log points lower. This possibly stems from sorting in equilibrium, since high-wage workers tend to sort into high-wage firms, thereby reducing the value of working somewhere else. Furthermore, it is known that workers at the top of the distribution tend to work for larger firms, which are also associated with more concentrated markets and, therefore, reduced alternatives for potential jobs.

I find that the quality of outside options is positively associated with wages, showing that a 10% increase in the average quality of other firms in the same market leads to a 3% increase in wages. However, after controlling for common market shocks, idiosyncratic shocks to outside options have a general negative impact on wages. This is consistent with search and matching mechanisms dating back to Postel-Vinay and Robin (2002), who show that firms tend to underpay workers at earlier tenures to insure against future wage raises from renegotiation. Indeed, I estimate stronger negative elasticities for new hires and less skilled workers, who are those who can reap more benefits from job ladder upgrades.

Lastly, I investigate how market structure can impact wage inequality. An extension to the AKM variance decomposition framework shows that market-year effects explain close to 15% of wage variance in Portugal from 2010 to 2021. Furthermore, the positive worker-firm sorting obtained from two-way fixed effects models is overestimated: part of its contribution to inequality stems from positive worker-market sorting.

These findings reinforce the fact that researchers should not neglect market structure when analyzing labor markets. Wages are determined not solely based on the policies of the current firm: other firms matter. Furthermore, they highlight how reduced-form models may cast aside relevant search-and-bargaining mechanisms if not properly accounted for.

Further research could incorporate other types of data to more solidly understand empirically how outside options can impact wages through search and renegotiation. Recent advancements include the work by Jäger et al. (2024) on improving information about outside options and the use of data on accepted and rejected offers by Guo (2024, 2025a). In general, further evidence on this matter could provide future guidance on policies regarding pay transparency across firms, improving job-search behavior and reducing labor market power.

TABLE 11. Elasticity of wages to other firms' pay premia, by occupation group

	(1) Managers	(2) Skilled Profs.	(3) Techn. & Ass. Profs	(4) Clerical Supp.	(5) Service & Sales	(6) Craft Trades	(7) Elementary Occupations
$\overline{\zeta}_{-fgt}$	-0.3106	-0.0409***	-0.0763***	-0.0713***	-0.1805***	-0.4097***	-0.3707***
	(0.2007)	(0.0147)	(0.0115)	(0.0119)	(0.0162)	(0.0112)	(0.0151)
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,170	1,623,555	1,166,348	1,906,094	3,395,158	1,811,558	1,193,078

Note: Coefficients from separate regressions for each occupation group. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level in parenthesis.
*** Denotes statistical significance at the 0.01 level.

TABLE 12. Elasticity of wages to other firms' pay premia, by industry

	(1) Manufacturing	(2) Construction	(3) Trade & Transport	(4) Accom. & Restaurants	(5) High VA Services	(6) Other Services
$\hat{\gamma}$	-0.0446***	-0.2709***	-0.0741***	-0.0459***	0.0090	-0.0031
	(0.0074)	(0.0132)	(0.0107)	(0.0138)	(0.0156)	(0.0102)
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Market-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighted?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,910,280	833,489	3,356,852	1,033,991	1,445,744	3,024,315

Note: Coefficients from separate regressions for each industry or group of industries. High VA services = Information and Communications; Financial Services; Real Estate Activities; Professional, Scientific and Technical Activities. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level.
*** Denotes statistical significance at the 0.01 level.

TABLE 13. Elasticity of wages to other firms' pay premia, by labor market concentration

	Low concentration		High concentration	
$\hat{\gamma}$	-0.2004***	-0.3258***	-0.1515***	-0.1118***
	(0.0109)	(0.0100)	(0.0057)	(0.0265)
Worker FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Market-Year FE	✓	✓	✓	✓
Split-Sample?	–	✓	–	✓
Weighted?	✓	✓	✓	✓
Observations	9,102,954	9,102,954	5,766,811	5,766,811

Note: Low concentration = 1 when peer group belongs to a labor market with HHI above the national median. Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm × year level.
*** Denotes statistical significance at the 0.01 level.

TABLE 14. Fixed effect covariances and contributions to $\mathbb{V}\left[w_{ifmt}\right]$

	Covariance	Share of total variance (%)
Two Fixed Effects		
Cov(Worker,Firm)	0.0384	13.07
Full Model		
Cov(Worker,Firm)	0.0310	10.50
Cov(Worker,Market-Year)	0.0256	8.71
Cov(Worker,LO Firm)	-0.0030	-1.04
Cov(Firm,Market-Year)	0.0068	2.33
Cov(Firm,LO Firm)	-0.0026	-0.91
Cov(Market-Year,LO Firm)	-0.0006	-0.22

Note: The full model shows the covariance between worker fixed effects, firm fixed effects, market-year fixed effects and the leave-out average of firms fixed effects (LO Firms). In both models, the worker fixed effects are adjusted for the linear effect of age and gender by residualizing $\hat{\alpha}_i$ on gender and year of birth dummies.

A. Auxiliary figures and tables

TABLE 15. Summary statistcs

	Mean	SD	P10	P50	P90
Wages					
Log real hourly wage	0.55	0.55	-0.01	0.39	1.32
Demographics					
Age	40.38	10.74	26.00	40.00	55.00
Share of Females	0.46	0.50	–	–	–
Education					
Less than High School	0.51	0.50	–	–	–
High School	0.31	0.46	–	–	–
College Degree	0.18	0.38	–	–	–
Employment					
Tenure (months)	103.39	107.09	5.00	64.00	263.00
Less than 10 Employees	0.25	0.43	–	–	–
10 to 50 Employees	0.26	0.44	–	–	–
50 to 250 Employees	0.22	0.41	–	–	–
More than 250 Employees	0.27	0.44	–	–	–

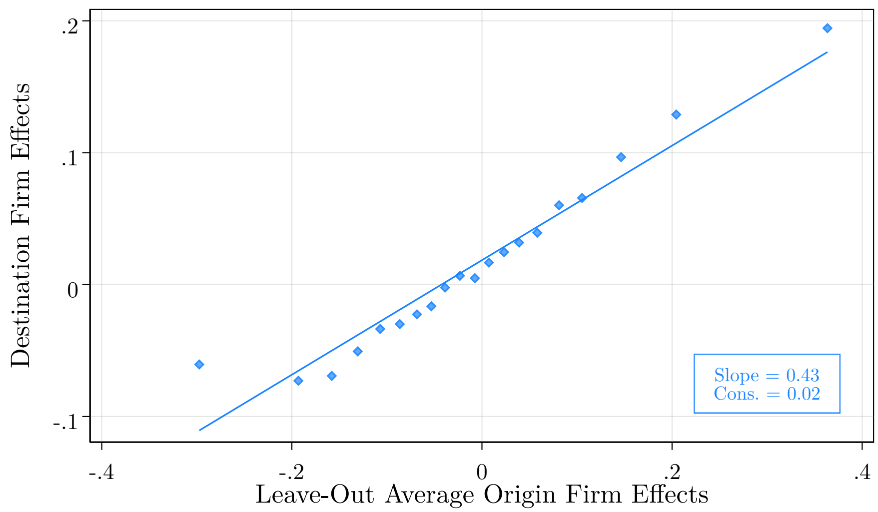


FIGURE 9. Destination and leave-out origin. All job movers.

FIGURE 10. Market-year fixed effects, 2010 vs. 2021, by sector

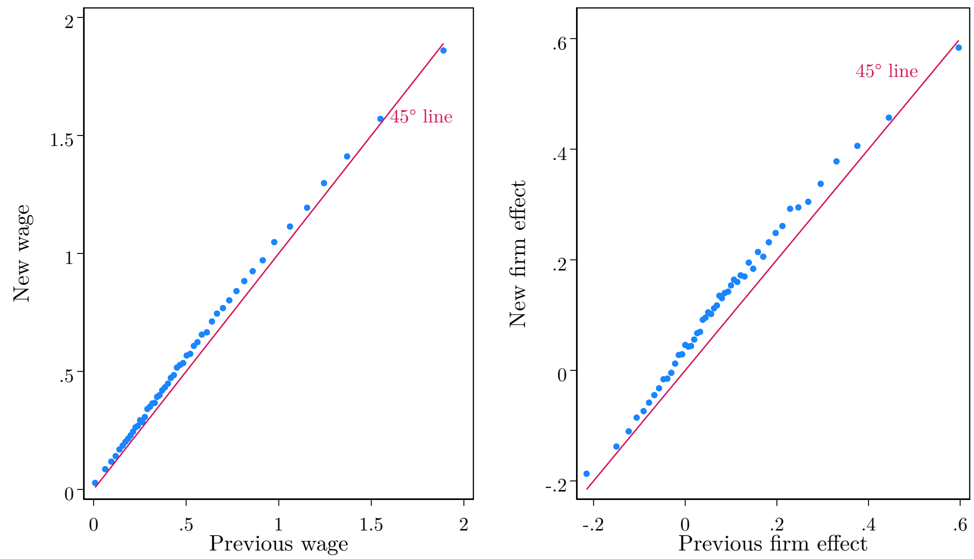


FIGURE 11. Movers: destination firm fixed effects vs. origin

TABLE 16. Elasticity of wages to other firms' pay premia, all coefficients

	(1)	(2)	(3)	(4)
Age sq.	0.0002***	0.0002***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0014***	0.0016***	0.0007***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure sq.	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.0043***	0.0056***	0.0020***	0.0025***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
$\bar{\zeta}_{-fgt}$	0.2117***	0.2784***	-0.0731***	-0.1002***
	(0.0038)	(0.0073)	(0.0045)	(0.0063)
Worker FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Market-Year FE	–	–	✓	✓
Split-Sample?	–	✓	–	✓
Weighted?	✓	✓	✓	✓
Observations	16,064,983	16,064,983	16,064,983	16,064,983

Note: Split-sample refers to incidental parameter bias adjusment as in Dhaene and Jochmans (2015). See Section 4.3.5 for details. Weighted indicates whether the average is weighted by market employment shares. Standard errors clustered at firm-year level.
*** Denotes statistical significance at the 0.01 level.

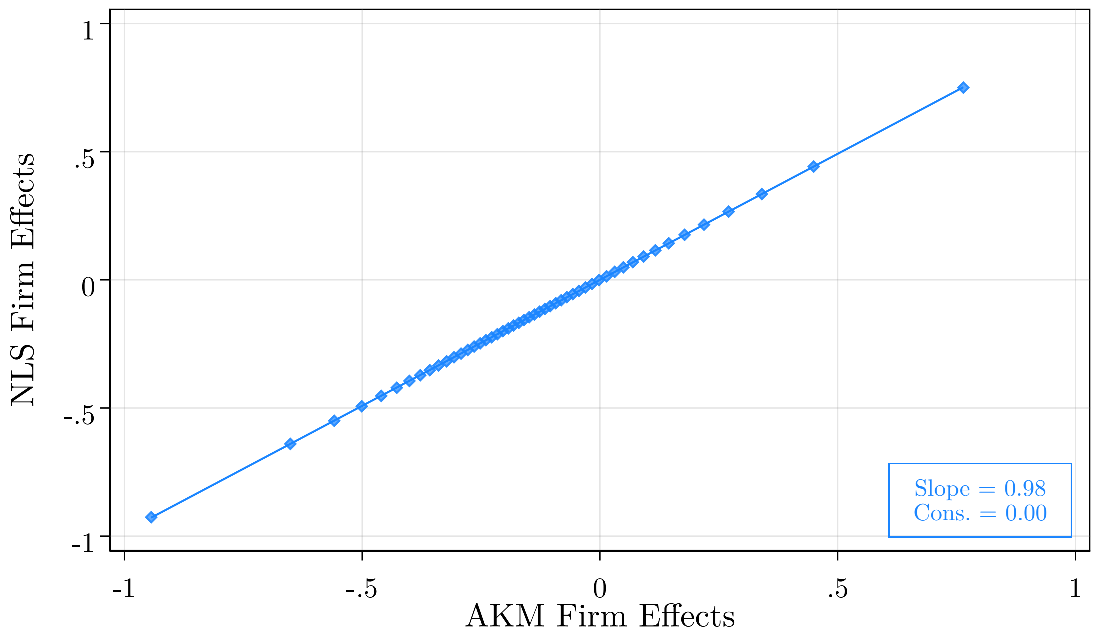


FIGURE 12. Firm Effects comparison: AKM versus NLS estimation.

TABLE 17. Variance decomposition, 2010-2021

	Variance Components	Contributions (%)
Var(Wages)	0.2942	
Worker		
Var(Worker)	0.1236	42.01
Cov(Worker,Firm)	0.0155	5.27
Cov(Worker,Market)	0.0128	4.35
Cov(Worker,OO)	-0.0015	-0.51
Cov(Worker,X)	0.0002	0.07
Firm		
Cov(Firm,Worker)	0.0155	5.27
Var(Firm)	0.0450	15.30
Cov(Firm,Market)	0.0034	1.16
Cov(Firm,OO)	-0.0013	-0.44
Cov(Firm,X)	-0.0007	-0.24
Market		
Cov(Market,Worker)	0.0128	4.35
Cov(Market,Firm)	0.0034	1.16
Var(Market)	0.0445	15.13
Cov(Market,OO)	-0.0003	-0.1
Cov(Market,X)	-0.0020	-0.68
Outside Options		
Cov(OO,Worker)	-0.0015	-0.51
Cov(OO,Firm)	-0.0013	-0.44
Cov(OO,Market)	-0.0003	-0.10
Var(OO)	0.0002	-0.07
Cov(OO,X)	-0.0001	-0.03
Covariates	0.0094	3.19
Residual	0.0260	8.85

Note: The worker fixed effects are adjusted for the linear effect of age and gender by residualizing $\hat{\alpha}_i$ on gender and year of birth dummies.

B. Variance decomposition bias correction

Recent studies have called attention to the need for bias correction in models with high-dimensional fixed effects due to the incidental parameter bias (Kline, Saggio, and Sølvsten 2020; Bonhomme et al. 2023). The authors have claimed this to be a problem stemming from limited mobility in the worker-firm network. Because worker and firm fixed effects are identified via firm-to-firm moves, lower mobility induces a high uncertainty in the estimation of the fixed effects, which leads to larger worker and firm fixed effect variances, to the detriment of covariances.

The most used bias correction techniques for the variance are those in Andrews et al. (2008) and Kline, Saggio, and Sølvsten (2020). Replicating the formulas in Bonhomme et al. (2023), consider the design matrix A, which represents the worker-firm-market graph of the network. Consider also $\xi = (\alpha, \zeta, \theta)$. Then, an estimator for ξ is

$$\hat{\xi} = (A'A)^{-1}A'W \tag{23}$$

The estimator for the variance components is, for some matrix Q:

$$\hat{V}_Q = \hat{\xi}'Q\hat{\xi} \tag{24}$$

The bias in $\hat{V}_Q$ can be written as

$$\mathbb{E}\left[\varepsilon'A(A'A)^{-1}Q(A'A)^{-1}A'\varepsilon\right] \tag{25}$$

The bias correction in Andrews et al. (2008) is constructed under the homoskedasticity assumption as

$$\hat{V}_Q^{HO} = \hat{V}_Q - \hat{\sigma}^2\text{Trace}\left((A'A)^{-1}Q\right) \tag{26}$$

The correction in Kline, Saggio, and Sølvsten (2020) relaxes the homoskedasticity assumption and is given by

$$\hat{V}_Q^{HO} = \hat{V}_Q - \text{Trace}\left(A(A'A)^{-1}Q(A'A)^{-1}A'\hat{\Omega}A\right), \tag{27}$$

where $\hat{\Omega}$ is a diagonal matrix with terms $\hat{\sigma} = W_{it}\left(W_{it} - \hat{\alpha}_i^{-(i,t)} - \hat{\zeta}_{f(i,t)}^{-(i,t)} - \hat{\theta}_{m(i,t)}^{-(i,t)}\right)$. $\hat{\sigma}$ is obtained from a leave-out jackknife procedure, where each observation (i, t) is removed from the sample sequentially. Kline, Saggio, and Sølvsten (2020) provide a simple way to avoid reestimating the model for millions of iterations.

Figure 13 shows the results from the estimator without bias correction (FE), with Andrews et al. (2008)'s correction (HO) and with Kline, Saggio, and Sølvsten (2020)'s correction

(HE).

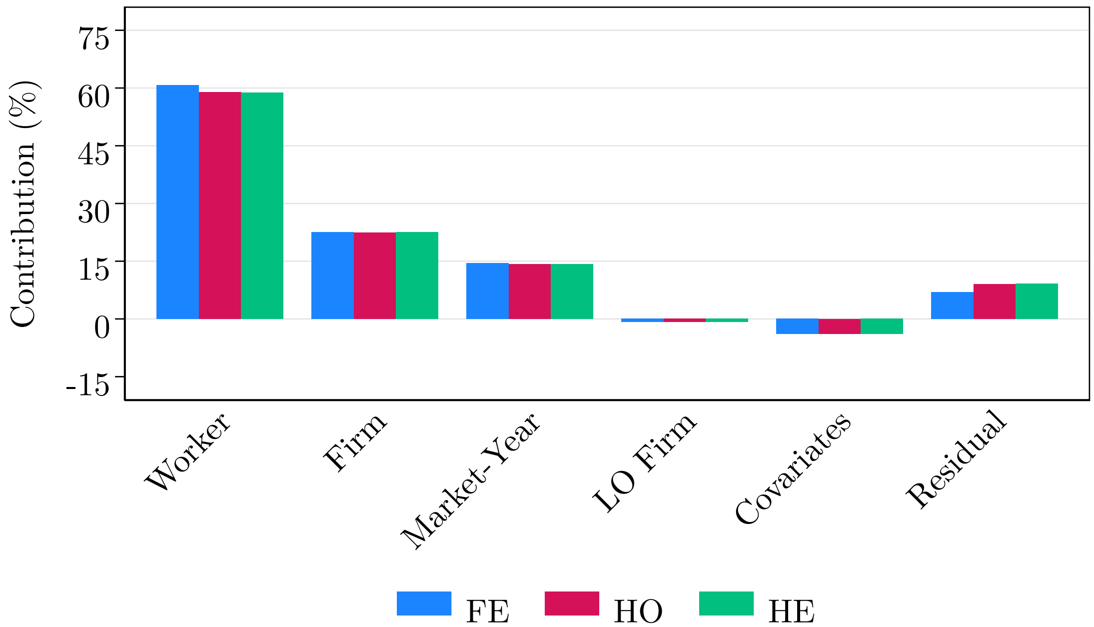


FIGURE 13. Firm Effects comparison: AKM versus NLS estimation.

Note: FE: non-linear least squares estimation without any bias adjustment correction for the variance or the coefficients; HO: bias in variance corrected according to Andrews et al. (2008); HE: bias in variance corrected according to Kline, Saggio, and Sølvsten (2020). The contribution of each component is calculated according to (22). Unlike the figures and tables in the main text, worker fixed effects are not adjusted for the linear effect of age and gender, which explains the differences between FE and the results in Figure 8.

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