Wage Bargaining and Wage Posting Firms

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Abstract

This paper studies the coexistence of two wage-setting regimes: wage posting and offer matching/wage bargaining. Based on a job-ladder model with both firm types, we develop a novel theoretically-informed maximum-likelihood clustering and estimation procedure that treats firms' wage-setting regimes as latent. Using German employer survey data to benchmark the classification and Austrian matched employer–employee records for estimation, we obtain consistent evidence across settings. Bargaining firms account for about 28% of firms in Austria and 24% in Germany; they are more productive and exhibit greater within-firm wage dispersion. The model explains job-to-job wage declines as workers transition from posting to bargaining firms, leading to inefficient mobility and output losses ranging from 13% to 36% of total output changes driven by job-to-job mobility. Counterfactuals show that segmenting labor markets by wage-setting regime raises wages relative to the mixed economy.

Keywords: Wage posting, Wage bargaining, Sequential auction, Random search, Wage dispersion
JEL codes: C78, E24, E25, J31, J41, M52

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1 Introduction

Building on the theoretical advancements that describe firms countering outside offers arising from on-the-job search (Postel-Vinay and Robin, 2002a,b), three key questions have emerged. First, how can firms engaging in such wage bargaining practices be distinguished from traditional wage-posting firms, as described by Burdett and Mortensen (1998); Bontemps et al. (2000), empirically? Second, what are the characteristics of wage bargaining and wage-posting firms? Third, what are the economic implications of the co-existence of the two firm types?

This paper addresses these questions by combining a tractable partial equilibrium model with a likelihood-based classification and estimation approach, and by bringing together survey and administrative data. On the theory side, we study a partial-equilibrium environment with on-the-job search in which a fraction of firms posts wages ("P-firms") and the remaining firms match outside offers ("M-firms"). The coexistence of the two protocols generates sharp directional implications that discipline identification: (i) within-firm wages are compressed at P-firms but disperse at M-firms due to renegotiation; (ii) $P \to P$ moves are associated with wage increases; (iii) $P \to M$ moves feature wage cuts at entry into the M-firm; and (iv) $M \to P$ moves occur only when posted contracts exceed the M-firm's retention ceiling. Because P-firms do not renegotiate, the model also allows for inefficient reallocation: some $P \to M$ transitions move workers to lower-productivity matches even as they raise continuation values.

On the empirical side, we proceed in two complementary steps. First, we document motivating evidence using German micro data that directly measure wage-setting at the vacancy. We use the IAB Job Vacancy Survey (JVS) linked to administrative worker histories, which allows us to (i) classify establishments based on whether pay was individually bargained at the most recent hire and whether the establishment is covered by collective agreements, and (ii) connect those survey-based classifications to within-firm wage distributions and to wage changes observed for workers who fill the surveyed vacancies. We find that bargaining firms are systematically different from wage-posting firms along three firm-level dimensions and one mobility dimension: bargaining firms have higher average wages and are more attractive employers (higher poaching ranks and lower exit ranks), exhibit greater within-firm wage dispersion, and more frequently report ex post upward compensation adjustments and negotiation over non-wage benefits; moreover, job-to-job movers switching from P- to M-firms are disproportionately likely to experience wage cuts, conditional on firm wage rank. We further characterize firm types based on observed characteristics. Our findings mostly align with prior empirical results from the literature (Brenčič, 2012; Brenzel et al., 2014; Caldwell and Harmon, 2019).

Second, we use Austrian matched employer–employee administrative data to estimate the model and recover firm types as latent variables. The key challenge is that administrative data do not report wage-setting institutions. We therefore derive the likelihood of observed wages and job-to-job transitions conditional on firm type and embed it in a latent-class mixture model at the firm level. Our estimation simultaneously (i) fits type-specific firm distributions (for the relevant firm characteristic) and model primitives governing labor search, and (ii) assigns each firm to be either M-firm versus P-firm. Operationally, we implement a classification-EM procedure in which the firm-type update combines a worker-level likelihood component (how well a firm's within-firm wage dispersion and the wage changes of its movers align with the M- versus P-regime) and a firm-level component implied by the firm type distributions. To accommodate measurement error and potential model misspecification, we relax the model's sharp restrictions by introducing deviation terms that capture wage and mobility disturbances. These terms play a role similar to measurement error in wages or unobserved mobility costs/amenities, allowing the estimation to depart from exact model equalities when warranted by the data. We choose the associated hyperparameters by maximizing the likelihood on a validation sample.

Our results deliver a consistent characterization of wage-setting regimes across the two countries and data sets and quantify their equilibrium implications. In Austria, we estimate that roughly 28% of firms are M-firms, close to the 24% share of bargaining firms in the German survey under our preferred definition. We therefore conclude that differential analysis of both firm types can be undertaken even in the absence of often costly and size-restricted surveys. The estimated M-firms occupy higher rungs of the job ladder: they are associated with higher recovered productivity and greater within-firm wage dispersion. Mobility patterns align with the model's sign restrictions: $P \to P$ moves are predominantly associated with wage gains, whereas $P \to M$ moves have a higher incidence of wage cuts. Importantly, the estimated coexistence of wage posting and offer matching has nontrivial allocative consequences. Inefficient $P \to M$ reallocation occurs for a non-negligible share of P-origin job-to-job movers, and the implied aggregate output loss is small in levels—about 0.01%—but economically meaningful relative to the gains generated by other worker flows in the model. Specifically, these losses amount to 13-36% of total absolute output changes generated by job-to-job mobility. Finally, we use the estimated model to run counterfactual wage schedules that vary the composition of firm types and the extent of cross-type competition. These counterfactuals imply that the coexistence of the two regimes can depress average wages relative to a segmented benchmark, highlighting that wage-setting institutions shape equilibrium wage pressure. A natural presumption is that greater market segmentation would weaken wage competition and thereby reduce wage pressure; in our setting, the opposite holds. Moreover, we find that an increase in the prevalence of M-firms lowers wages at P-firms, showing that wage posting firms benefit from the existence of M-firms all else equal.

Beyond documenting a new set of facts, the paper contributes methodologically and substantively to several literatures. First, it contributes to work on wage posting and wage bargaining with on-the-job search (Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002a,b, 2004; Flinn and Mullins, 2021; Doniger, 2023) by providing an empirical strategy to recover wage-setting regimes as latent firm types using administrative data, disciplined by model-implied likelihoods and validated against survey measures of bargaining. Second, it speaks to the literature using linked data and surveys to characterize wage-setting practices and their consequences (Hall and Krueger, 2012; Brenzel et al., 2014; Brenčič, 2012; Caldwell and Harmon, 2019), by showing that mobility-related wage changes provide an additional, powerful dimension for distinguishing protocols. Third, it connects to recent work using likelihood-based clustering to recover latent firm structure (Bonhomme et al., 2019, 2023; Lentz et al., 2023), but targets differences in wage-setting institutions rather than differences in wage premia or productivity alone. Finally, the framework offers a unifying interpretation of classic variance-decomposition evidence based on origin and destination firms: in our model, the relative importance of origin versus destination in wage changes is naturally type-dependent, so pooled estimates can mask distinct mechanisms operating in posting and bargaining regimes (Lachowska et al., 2022). The closest related paper is Flinn and Mullins (2021), who develop and estimate a search model in which firms choose, at vacancy creation, between posting a non-negotiable wage and bargaining/renegotiating with workers, and use the estimated model to evaluate counterfactual wage-setting mandates and their implications for inequality, welfare, and output. Our contribution is complementary but differs along three dimensions. First, while Flinn and Mullins (2021) emphasize cross-market variation in bargaining prevalence—treating demographic cells as segmented labor markets and estimating the model at that level—our objective is to recover within-market heterogeneity by classifying individual firms into wage-posting and wage-bargaining types in matched employer–employee data. Second, methodologically, we propose a likelihood-based latent-type classification procedure that jointly disciplines firm types using within-firm wage dispersion and mobility-linked wage changes, and we validate the resulting classifications against direct survey measures of wage-setting protocols from linked German vacancy data; this contrasts with the market-level identification approach in Flinn and Mullins (2021). Third, our quantitative focus is on the implications of cross-type mobility and the wage-schedule consequences of coexistence in administrative data settings where wage-setting protocols are not directly observed, rather than on policy mandates and inequality decompositions across demographic markets.

The remainder of the paper is organized as follows. Section 2 presents motivating evidence from German survey-linked micro data. Section 3 develops the model and derives the directional implications for within-firm wage dispersion and wage changes on mobility. Section 4 describes the Austrian data used for estimation. Section 5 describes the likelihood, the latent-type estimation, and the clustering algorithm. Section 6 reports the Austrian estimates, validates the recovered firm types against the German evidence, and quantifies the allocative and wage effects of cross-type competition. Section 7 concludes.

2 Motivating Evidence

This section presents empirical evidence, using German microeconomic data, on the coexistence of two distinct wage-setting regimes: wage posting and wage bargaining. After describing the data, we present four empirical facts that summarize our main findings—three capturing firm-level characteristics, and one documenting wage changes among job movers who transition between firm types.

Data Sets and Variables We use the job vacancy survey (JVS), together with firm and worker-level panel data from the Research Data Centre at the *Institut für Arbeitsmarkt- und Berufsforschung der Bundesagentur für Arbeit* (IAB).[1] A more detailed description of the data can be found in Online Appendix section B. A version of the JVS data set merged with the IABSE-ADIAB has previously been used in Carlos Carrillo-Tudela and Lochner (2023). The JVS has previously been used in an early variant in Brenzel et al. (2014).

For the years 2011-2013 and 2016-2019, the JVS contains questions on wage and compensation bargaining at filled and unfilled vacancies, obtained through a firm survey. We rely on two types of record matches. First, the data links survey information on vacancies to firm-level employment data. Second, it connects the survey information on vacancies to the labor market trajectories of workers who filled them. We focus on four questions from the survey on filled vacancies:

1. Bargaining: Did you bargain over compensation?
2. Collective Agreement: Is there a sector, firm or establishment-level collective bargaining agreement in place?

[1] Throughout, we refer to the IAB establishment as 'firm' for readability.

3. Pay More: Did you have to pay more than expected?
4. Other remuneration: Was there additional remuneration (in kind or financial) offered?[2]

With the linked survey-worker panel data, we observe a rich set of worker characteristics, including education and gender, as well as firm-level attributes such as industry and geographic location. We also observe the worker wage, measured as total pay divided by days worked. To proxy for firm wage rank/quality in the linked survey-worker panel data, we control for coworker average wage. In the linked survey-firm panel, we observe counts of worker inflows and outflows at the firm level, enabling the construction of revealed-preference measures such as poaching rank (Bagger and Lentz, 2018) and exit rank (Morchio and Moser, 2024). The analysis is conducted at an annual frequency, at the level of the worker-firm match.[3]

We classify a firm as a bargaining firm based on responses to survey questions 1 and 2, subject to two criteria. First, a majority of responses within the firm (across workers and years) must report that wages were individually bargained (cf. question 1). Second, the firm must not be covered by a collective bargaining agreement at the sector, firm, or establishment level (across years, cf. question 2). In our main specification, we consider a constant firm classification across all years to reduce misclassifications from small samples but also report results for individual years. We follow this double characterization as we aim to capture individual bargaining between the firm and the worker, not between unions or worker representatives, in a consistent way.[4] Our classification is designed to isolate individual bargaining; the residual group includes collectively bargained settings. We treat collectively bargained settings as closer to wage posting in the sense that pay is set by a schedule rather than bilateral negotiation at the vacancy. In robustness specifications, we will consider bargaining firms as those only satisfying question 1. In addition, we will later examine whether our firm classification aligns with theoretical expectations.

Using our classification, we focus on two analyses. First, when matching the JVS to firm level data, we can study average characteristics of bargaining and wage-posting firms. Second, when combining the JVS with worker panel data, we can observe the labor market history of workers and identify a switch in the bargaining type of the firm during a job move. We distinguish between job moves from bargaining or offer-matching firms (M) to wage-posting (P) firm ($M2P$ mobility) as well as vice versa ($P2M$ mobility) and job moves that stay within the same type of firm ($M2M$, $P2P$ mobility). We are particularly interested in

[2]Note that this question is available in all years except 2013.

[3]Note that the linked survey-worker panel data cannot be merged to the survey-firm panel at the time of writing.

[4]Accordingly, we deviate from the classification used in Brenzel et al. (2014), where firms covered by collective bargaining agreements are, in some cases, grouped together with bargaining firms.

the probability of wage decreases among the different types of moves. Since bargaining firms enable wage negotiations, they offer the option value of expected wage growth with tenure—something that wage-posting firms cannot provide. Consequently, mobility from P to M-firms may result in an initial wage decrease. We would like to test for this mechanism in our data.

Firm Characteristics We begin by examining how non-bargaining (wage-posting) firms differ from bargaining firms, using firm-level data merged with the Job Vacancy Survey (JVS). Weighted summary statistics by firm type, as well as for the full sample, are reported in Online Appendix Table 1. In this table, ”Bargaining” corresponds to responses to question 1, while ”Bargaining+” reflects our preferred classification based on both questions 1 and 2. On average, 24 percent of firms are classified as M-firms under this definition.

We document three findings. First, we find that bargaining firms offer higher average daily log wages (4.56 instead of 4.49) and are more attractive to workers, as reflected in their higher poaching ranks (0.55 instead of 0.50) and lower exit ranks (0.36 instead of 0.39). Second, M-firms exhibit a wider wage dispersion, as measured by the inter-quartile range of log wages within the firm (the difference between the 75th and 25th percentiles, with 0.34 instead of 0.31), than P-firms. Third, bargaining firms more frequently report paying above initially intended wages to secure a hire (30% as compared to 10%). In addition, they more often report to bargain also on other forms of compensation (52% as compared to 40%). We observe that these firms have a slightly lower share of female employees (42% as compared to 44%), are on average smaller (115 as compared to 402 employees) and are more often in the service sector (60% as compared to 52%). To compare our estimates to previous work using the JVS in Brenzel et al. (2014), we report average statistics across different survey years in Online Appendix Table A.2. Consistent with Brenzel et al. (2014), we find that approximately 37 % of workers reported having negotiated their salary in 2011, based on responses to question 1. Using our preferred classification—based on both questions 1 and 2—we estimate that 19 % of firms were bargaining firms in that year. Notably, the prevalence of individual wage negotiation has steadily increased over time. Between 2011 and 2019, the (weighted) share of firms classified as bargaining firms rose by 10 percentage points in our sample.

Wage Decreases and Worker Mobility We next consider the probability of wage decreases given different types of mobility, using the JVS together with the worker level panel data set. As we will elaborate in the theoretical section, transitions from P- to M-firms may involve a trade-off between higher current wages at P-firms and the prospect of future wage growth

	All	P-Firms	M-Firms
Bargaining +	0.24	0.00	1.00
Bargaining	0.42	0.23	1.00
Size	334.06	401.88	115.76
Wage	4.51	4.49	4.56
Poachingrank	0.51	0.50	0.55
Exitranking	0.38	0.39	0.36
Spread Wages	0.31	0.31	0.34
25 Percentile	4.30	4.29	4.34
75 Percentile	4.62	4.60	4.68
Services	0.54	0.52	0.60
East	0.19	0.19	0.19
Coll.Agreem.	0.57	0.74	0.00
Pay More	0.15	0.10	0.30
Female Share	0.43	0.44	0.42
Other Ren.	0.43	0.40	0.52
# Firms	59423	45001	14422

Table 1: Summary Statistics

Note: The table contains summary statistics on wage-bargaining (M) and wage-posting (P) firms. Wage spread denotes the difference between the 75th and the 25th percentile of log wages. "Bargaining" refers to question 1, whereas "Bargaining+" refers to our preferred classification using both questions 1 and 2. All statistics are weighted using survey weights. 'Other Ren.' is one if there was negotiation also on other forms of remuneration.

at M-firms. In addition, transitions from M to M-firms could lead to wage decreases upon mobility due to higher option values at better firms.

Our analysis restricts attention to job movers employed at firms with at least two employees, ensuring that coworker average wages are well-defined. To capture likely job-to-job moves, we exclude individuals who report having been laid off from their previous employer and restrict the gap between employment spells to no more than 15 days. Our mover sample consists mostly of workers at P-firms which is in line with movers being concentrated at lower ranks of the job ladder. Summary statistics of the data set can be found in Online Appendix Table A.3. We find that 33% of movers experience a wage decrease upon mobility, in line with previous estimates in Sorkin (2018). Most workers stay in their respective firm type upon mobility (86%). Among firm-type changers, most move from a P to an M firm (8% of movers).[5]

[5] In Online Appendix Table A.4, we further analyze the whole matched data set in order to describe differences in worker characteristics across firm types. We find that M-firms have a higher share of workers with high school degree (but a lower share of workers with baccalaureate), less workers with temporary or

Our baseline analysis examines the likelihood of a wage decline following job-to-job transitions, distinguishing between within-type moves ($M2M$ or $P2P$) and across-type moves ($P2M$ or $M2P$). Firm types are classified as in the previous section, based on responses to survey questions 1 and 2. Specifically, we estimate a linear probability model in which the dependent variable is an indicator for a wage decline, $I_{\Delta w<0}$, and the key regressors capture the type of firm-to-firm transition. Hence, we test whether worker i is more likely to experience a wage cut at time t following a $P2M$, $M2P$, or within-type ($M2M$ or $P2P$) move. The omitted category is $M2P$ mobility.

$$I\{\Delta w < 0\}_{i,t} = \alpha_{P2M} I\{P2M\} + \alpha_{\text{Firm-Type Stayer}} I\{\text{Firm-Type Stayer}\} + x_{i,t}\beta + \epsilon_{i,t}$$

Table 2 summarizes the regression coefficients. In column one we report the baseline estimate, without any controls. We find that a $P2M$ transition is more likely to be associated with a wage decrease than a within-firm-type transition. Informed by the summary statistics of the previous paragraph, we know that M-firms are on average higher ranked and possibly more productive firms. The probability of a wage decrease will therefore depend on the firm ranking, such that we control for firm quality, using the average coworker wage, in column (2), for both origin and destination firm. In column (3) we add further control variables for education, gender, age and firm location (east/west). In column (4) we add year fixed effects, and adopt a logit specification instead in column (5) to (6). In column (6) we control whether the firm offered other forms of compensation as well. Online Appendix Table A.5 further subdivides the categories for firm type stayers, finding higher likelihoods of wage decreases for $M2M$ than $P2P$ transitions, as consistent with theoretical expectations. In Online Appendix Table A.6 we show that this equally holds when using only question 1 to define a bargaining firm, with even starker results regarding the effect of firm type. Overall, our fourth finding is that, conditional on firm quality, P-to-M mobility events are more likely to involve wage decreases than other mobility events.

Further Indications for Wage Posting/ Wage Bargaining A potential concern is that the identified firm types may not fully capture the distinction between wage bargaining and wage posting firms as understood in the literature. To address this concern, we conduct three additional tests consistent with the coexistence of both types of firms. First, we document that M-firms exhibit higher residual wage growth among job stayers, conditional on observable characteristics (including education, gender, age, region—East or West Germany—and year, results shown in Table A.7). Second, we find that the variance of residual wages, after

part-time contracts. These findings are partly consistent with (Brenčič, 2012) and (Brenzel et al., 2014) who describe M-firms as more likely to hire high-skill workers.

	(1)	(2)	(3)	(4)	(5)	(6)
$P2M$	0.0527^{*}	0.103^{*}	0.101^{*}	0.1000^{*}	0.473^{*}	0.475^{*}
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM/PP	0.0217^{+}	0.0527^{*}	0.0583^{*}	0.0592^{*}	0.281^{*}	0.282^{*}
	(0.096)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	38806	38806	38806	38806	38806	38806
Controls		+Firm Q.	+Demo	+Year	Logit	+ Other Ren.

p-values in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$

Table 2: Probability Wage Decrease Upon Mobility based on Mobility Type

Note: The table contains regression coefficients of the probability of wage decreases upon mobility on the type of mobility. We choose the $M2P$ mobility as our baseline contrast. Columns 1-4 present coefficients in a linear probability model whereas columns 5-6 show results for a logit model. "Demo" refers to demographics education, gender, age, firm location (east/west). "Other Ren" refers to the offer of other remunerations.

conditioning on observables, is greater within M-firms than within P-firms (results shown in table A.8). Third, we show that separation rates in M-firms are less responsive to a firm's residual wage rank (conditional on observables) than in P-firms, consistent with theoretical predictions (results shown in table A.9). These results are collected in Online Appendix section C.1.

Summary We document four facts consistent with a mixture of wage posting and wage bargaining regimes in German firms.

- M-firms are, on average, higher-wage and more attractive employers, as indicated by higher poaching ranks and lower exit ranks.
- M-firms exhibit greater within-firm wage dispersion than P-firms.
- M-firms more frequently report compensation adjustments—paying more than intended to secure hires—and are more likely to negotiate additional forms of remuneration.
- Among job-to-job movers, transitions from P-firms to M-firms are disproportionately associated with wage cuts, even after controlling for origin and destination firm wage rank using coworker average wages.

Taken together, these facts suggest that wage-setting in German firms is well-described by a mixture of two regimes: one with compressed within-firm wages and predominantly upward wage changes on job-to-job moves, and another with greater within-firm dispersion and a higher incidence of wage cuts on certain transitions. In Sections 3–5, we formalize these directional implications in a model with wage posting and offer matching, and later impose them as soft restrictions in our Austrian estimation. While many previous studies have discussed differences in average firm characteristics at wage-posting and wage-bargaining firms in line with our estimates (Brenčič, 2012; Brenzel et al., 2014; Hall and Krueger, 2012; Caldwell and Harmon, 2019), none have discussed differences in mobility patterns to distinguish them. We will use these characteristics in our estimation exercise. To develop this argument, we describe the theoretical setting in the next sections.

3 Theoretical Framework

This section develops the model's equilibrium objects. Section 3.1 characterizes workers' value functions at wage-posting and wage-bargaining firms. Section 3.2 derives the steady-state wage distributions, and Section 3.3 characterizes equilibrium wage policies and within-firm distributions. These results jointly pin down mobility across firm types and its implications for wages. Section 3.4 summarizes the theoretical predictions used in the estimation procedure. Table A.1 in the Online Appendix lists the main notation.

3.1 Values

Workers are homogeneous. Firms differ by productivity p and their wage setting mechanism. Posting firms are called P-firms and matching firms (or bargaining firms) are called M-firms. A fraction $\xi_M = \xi$ of firms match outside offers; a fraction $\xi_P = 1 - \xi$ post wages. The distribution of productivities among M-firms is Γ with support on the interval $[\underline{p}, \overline{p}]$. A P-firm contract is summarized by its worker value W, i.e. the present discounted value of the employment relationship. The equilibrium distribution of contract values offered by P-firms is F with support on the interval $[\underline{W}, \overline{W}]$.

Unemployment. Unemployed workers meet vacancies at frequency λ. There is no continuation value for meetings with M-firms because M-firms only need to match the value of unemployment. The value of unemployment V_0 then satisfies the following option value equation,

$$rV_0 = b + \lambda(1 - \xi)P(V_0), \tag{1}$$

where b is the unemployment benefit and P is the Emax operator giving the expected net gain from contacting a P-firm:

$$P(W) = \mathrm{E}_{W' \sim F} \max\{W', W\} - W = \int_{\underline{W}}^{\overline{W}} \max\{W' - W, 0\} \, \mathrm{d}F(W') = \int_{W}^{\overline{W}} \overline{F}(W') dW'. \quad (2)$$

Note that this formula allows for $W < \underline{W}$ and $W > \overline{W}$ as we integrate over $F(W)$. Lastly, P is differentiable with $P'(W) = -\overline{F}(W)$.

Posting firms' wage contracts. Let κ denote the relative search intensity of employees relative to unemployed workers. Let $w_P(W)$ denote the wage paid by a posting firm that promised a value $W \in [\underline{W}, \overline{W}]$. The following option value equation links $w_P(W)$ to W,

$$(r + \delta)W = w_P(W) + \delta V_0 + \kappa\lambda(1 - \xi)P(W). \quad (3)$$

The continuation value is derived as follows. With probability $\kappa\lambda(1 - \xi)$ the worker meets a posting firm offering W', which is accepted if $W' > W$. With probability $\kappa\lambda\xi$ she meets a matching firm who just needs to match the current contract W.

We have

$$w_P'(W) = r + \delta + \kappa\lambda(1 - \xi)\overline{F}(W) > 0.$$

The function w_P is therefore increasing.

Matching firms' values. The maximal value in a matching firm with productivity p is $S(p) = S$ such that,

$$(r + \delta)S = p + \delta V_0 + \kappa\lambda(1 - \xi)P(S), \quad (4)$$

with no continuation from meeting M-firms because matching poachers will not bid above $S(p)$. The function S is differentiable and increasing with

$$S'(p) = \frac{1}{r + \delta + \kappa\lambda(1 - \xi)\overline{F} \circ S(p)} > 0.$$

Note that, for all $W \in [\underline{W}, \overline{W}]$,

$$S^{-1}(W) = (r + \delta)W - \delta V_0 - \kappa\lambda(1 - \xi)P(W) = w_P(W).$$

$S^{-1}(W)$ is the minimum productivity of an M-firm outbidding a P-firm offering value W. It is therefore also the wage at a P-firm offering value W. It follows that if F is the distribution of contracts W offered by posting firms, then $\Psi := F \circ S$ is the distribution of wage offers $S^{-1}(W)$. Finally, note that $S^{-1}(W) = w_P(W) \leq p$. Hence, all M-firms with productivity p' in the range $[S^{-1}(W), p[$ will poach workers from P-firms with productivity p, resulting in inefficient moves.

Proposition 1 (Inefficient mobility)**.** *Any P-firm with productivity p and offering contract W will lose workers to M-firms with productivity $p' \geq S^{-1}(W) = w_P(W)$, allowing for inefficient firm-to-firm moves when $p' < p$.*

Matching firms' wage contracts. Now, consider a worker employed at a matching firm p with a contract $W \leq S(p)$. This contract may result from hiring the worker out of unemployment, or from poaching out of a firm posting W, or from poaching out of a matching firm $q \leq p$, in which case $W = S(q)$. The current wage is $w = w_M(W, p)$ such that

$$(r + \delta)W = w_M(W, p) + \delta V_0 + \kappa\lambda(1 - \xi)P(W) + \kappa\lambda\xi M(W, p),$$

where $M(W, p)$ is the Emax operator giving the expected net gain for the worker of the Second Price Auction:

$$M(W, p) = \mathrm{E}_{p' \sim \Gamma} \max\{\min\{S(p'), S(p)\} - W, 0\} = \int_{\underline{p}}^{p} \max\{S(p') - W, 0\} \,\mathrm{d}\Gamma(p') + [S(p) - W]\, \overline{\Gamma}(p),$$

that is, after integrating by part,

$$M(W, p) = \int_{S^{-1}(W)}^{p} \overline{\Gamma}(p') \,\mathrm{d}S(p').$$

Note that it could be that $S^{-1}(W) < \underline{p}$.

We have

$$\begin{aligned}
\frac{\partial w_M(W, p)}{\partial W} &= r + \delta + \lambda\kappa(1 - \xi)\overline{F}(W) + \lambda\kappa\xi\overline{\Gamma}\left(S^{-1}(W)\right) > 0, \\
\frac{\partial w_M(W, p)}{\partial p} &= -\frac{\lambda\kappa\xi\overline{\Gamma}(p)}{r + \delta + \lambda\kappa(1 - \xi)\overline{F}\left(S(p)\right)} < 0.
\end{aligned}$$

Link between wage functions. Note that

$$w_M(W, p) = w_P(W) - \kappa\lambda\xi \int_{w_P(W)}^{p} \overline{\Gamma}(p') \,\mathrm{d}S(p') = T\left(w_P(W), p\right),$$

since $w_P = S^{-1}$ and defining

$$T(w,p) = w - \kappa\lambda\xi \int_w^p \overline{\Gamma}(x) S'(x)\,\mathrm{d}x$$
$$= w - \int_w^p \frac{\lambda\kappa\xi\overline{\Gamma}(x)}{r + \delta + \kappa\lambda(1-\xi)\overline{F}\circ S(x)}\,\mathrm{d}x. \tag{5}$$

$T(w,p)$ is the minimum wage that a matching firm p must offer to a worker currently employed at a posting firm with wage w to attract her.

Matching firms pay less than posting firms for the same contract value (i.e. $w_M(W,p) \leq w_P(W)$) because wages in matching firms are implicitly increasing with tenure. It also follows that workers moving from a posting to a matching firm (therefore at the same value W) will always face a wage cut.

Proposition 2 (Transitions with Wage Cut)**.** *Transitions from P-firms to M-firms occur with a wage cut.*

Corollary 1 (Sign restriction for moves out of posting firms)**.** *Consider a worker employed at a P-firm with contract value W and wage $w_P(W)$. Any accepted outside offer implies:*

1. *if the destination is a P-firm offering $W' > W$, then $w' = w_P(W') > w_P(W)$, so $\Delta w > 0$;*
2. *if the destination is an M-firm with productivity p', then $w' = w_M(W,p') = T(w_P(W),p') \leq w_P(W)$, so $\Delta w \leq 0$ (with strict inequality whenever $p' > w_P(W)$).*

Hence, conditional on a P-firm origin, $\Delta w < 0$ implies a transition to an M-firm, while $\Delta w > 0$ implies a transition to a P-firm.

3.2 Steady-State Distributions

We now consider the distribution of contracts and employer characteristics in the total labor force. We normalize the measure of workers to one. Let n be the measure of employees of posting firms, and $G(W)$ is the distribution of contracts. Let m be the measure of employees of matching firms, and $L(p)$ is the distribution of productivity among employees. Let u be the measure of unemployed and $1 - u = m + n$ is the measure of all employees.

3.2.1 Flow equations

Unemployment. Equating flows from and to unemployment yields

$$\lambda u = \delta(n+m).$$

Posting jobs. For posting jobs, we have

$$nG(W)\left[\delta+\kappa\lambda(1-\xi)\overline{F}(W)\right]+n\kappa\lambda\xi\int_{\underline{W}}^{W}\overline{\Gamma}\circ S^{-1}(W')\,\mathrm{d}G(W')$$
$$=u\lambda(1-\xi)F(W)+m\kappa\lambda(1-\xi)\int_{\underline{p}}^{S^{-1}(W)}\left[F(W)-F\circ S(p)\right]\mathrm{d}L(p).$$

Matching jobs. For matching jobs,

$$mL(p)\left[\delta+\kappa\lambda\xi\overline{\Gamma}(p)\right]+m\kappa\lambda(1-\xi)\int_{\underline{p}}^{p}\overline{F}\circ S(p')\,\mathrm{d}L(p')$$
$$=u\lambda\xi\Gamma(p)+n\kappa\lambda\xi\int_{\underline{W}}^{S(p)}\left[\Gamma(p)-\Gamma\circ S^{-1}(W)\right]\mathrm{d}G(W).$$

3.2.2 Solution

Set $W=S(p)$ and add both flow equations. We obtain

$$\left[mL(p)+nG\circ S(p)\right]\left[\delta+\kappa\lambda(1-\xi)\overline{F}\circ S(p)+\kappa\lambda\xi\overline{\Gamma}(p)\right]=u\lambda\left[(1-\xi)F\circ S(p)+\xi\Gamma(p)\right],$$

or

$$\frac{m}{m+n}L(p)+\frac{n}{m+n}G\circ S(p)=\frac{\delta K(p)}{\delta+\kappa\lambda\overline{K}(p)}, \tag{6}$$

with the notation

$$K(\theta)=(1-\xi)F\circ S(\theta)+\xi\Gamma(\theta). \tag{7}$$

$K(\theta)$ has an interesting interpretation. As already stated, $\Psi(w)=F\circ S(w)$ is the distribution of wages offered by P-firms. $\Gamma(p)$ is the distribution of job output at M-firms. Let θ be the wage offer if P-firm, and the match output if M-firm. Our estimation procedure will measure θ by the average wage in the firm if P-firm, and by the maximum wage if M-firm. The left-hand side of equation (6) is the distribution of θ across employees, and $K(\theta)$ is the distribution of θ across firms.

Then, either one of the steady-state flow equations by market yields the equilibrium solution for L, after differentiation,

$$\frac{m}{m+n}L'(p) = \frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(p)\right]^2}\xi\Gamma'(p), \tag{8}$$

and the equilibrium solution for G follows as

$$\frac{n}{m+n}(G\circ S)'(w) = \frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(w)\right]^2}(1-\xi)(F\circ S)'(w), \tag{9}$$

where w is any wage offer.

To obtain the equilibrium market shares $\frac{m}{n+m}$, $\frac{n}{n+m}$, it suffices to integrate these equations. For example,

$$\frac{m}{n+m} = \int \frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(p)\right]^2}\xi\,\mathrm{d}\Gamma(p). \tag{10}$$

Let N denote the total number of active firms. The size of a P-firm offering wage w is

$$\ell_P(w) = \frac{n(G\circ S)'(w)}{N(1-\xi)(F\circ S)'(w)} = \frac{n+m}{N}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(w)\right]^2}.$$

The size of an M-firm with productivity p is

$$\ell_M(p) = \frac{mL'(p)}{N\xi\gamma(p)} = \frac{n+m}{N}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(p)\right]^2}.$$

Firm sizes are increasing in wages and productivity.

3.3 Equilibrium Wage Policies and Within-Firm Distributions

Wage posting equilibrium. Given other firms value distribution F, a posting firm of productivity p chooses the wage offer w that solves

$$\pi(p) = \max_w \frac{p-w}{\left[\delta+\lambda\kappa\overline{K}(w)\right]^2} \tag{11}$$

subject to the worker participation constraint

$$W = S(w) \geq V_0.$$

Here $K = (1-\xi)\Psi + \xi\Gamma$, with $\Psi = F \circ S$ and $\psi = \Psi'$. The first-order condition is

$$2(p-w)\frac{\lambda\kappa k(w)}{\delta + \lambda\kappa\overline{K}(w)} = 1. \tag{12}$$

The Nash equilibrium is a function $w = q(p)$ such that $\Psi(q(p)) = \Gamma_P(p)$ and

$$2\left[p - q(p)\right]\frac{\lambda\kappa k(q(p))}{\delta + \lambda\kappa\overline{K}(q(p))} = 1 \tag{13}$$

where

$$\begin{aligned}
\overline{K}(q(p)) &= (1-\xi)\overline{\Psi}(q(p)) + \xi\overline{\Gamma}(q(p)) = (1-\xi)\overline{\Gamma}_P(p) + \xi\overline{\Gamma}(q(p)),\\
k(q(p)) &= (1-\xi)\psi(q(p)) + \xi\gamma(q(p)) = (1-\xi)\frac{\gamma_P(p)}{q'(p)} + \xi\gamma(q(p))
\end{aligned}$$

The equilibrium wage function is therefore the solution to the first-order non-linear differential equation

$$q'(p) = \frac{2\left[p-q(p)\right]\lambda\kappa(1-\xi)\gamma_P(p)}{\delta + \lambda\kappa\left[(1-\xi)\overline{\Gamma}_P(p) + \xi\left(\overline{\Gamma}(q(p)) - 2\left[p-q(p)\right]\gamma(q(p))\right)\right]}. \tag{14}$$

The ODE is solved on the support $[p_0, p_1]$ of Γ_P, with initial condition $q(p_0) = \underline{w}$. The lower bound $\underline{w}$ is pinned down by the participation constraint $\underline{w} = S^{-1}(V_0)$.

In practice, we proceed as follows. For a candidate $\underline{w}$, we solve the differential equation numerically, recover $\Psi(w) = \Gamma_P(q^{-1}(w))$, and compute the implied continuation value. We then update $\underline{w}$ until it satisfies

$$\underline{w} = S^{-1}(V_0) = b + (1-\kappa)\lambda(1-\xi)\int_{\underline{w}}^{\overline{w}} \frac{\overline{\Psi}(w)dw}{r + \delta + \lambda\kappa(1-\xi)\overline{\Psi}(w)},$$

where $\Psi(w) = \Gamma_P(q^{-1}(w))$.

Within matching firm's distribution of job values. Let $G(W|p)$ be the distribution of employees' job values W within a matching firm of productivity p. We can write the following flow condition: for $\underline{W} \leq W \leq S(p)$, with $l(p) = L'(p)$,

$$\begin{aligned}
&ml(p)G(W|p)\left[\delta + \kappa\lambda\xi\overline{\Gamma}\left(S^{-1}(W)\right) + \kappa\lambda(1-\xi)\overline{F}(W)\right]\\
&= \left[u\lambda + \kappa\lambda mL\left(S^{-1}(W)\right) + \kappa\lambda nG(W)\right]\xi\gamma(p) = \left[(n+m)\delta + \kappa\lambda mL\left(S^{-1}(W)\right) + \kappa\lambda nG(W)\right]\xi\gamma(p).
\end{aligned}$$

Changing $W = S(t)$ and using equation (6), we have,

$$ml(p)G\left(S(t)|p\right) = (n+m)\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(t)\right]^2}\xi\gamma(p).$$

The wage distribution in any M-firm of productivity p is the distribution of $w = T(t,p)$, where t has distribution

$$\mathcal{G}(t|p) = \left[\frac{\delta+\kappa\lambda\overline{K}(p)}{\delta+\kappa\lambda\overline{K}(t)}\right]^2, \tag{15}$$

for $t \in [\underline{w}, p]$, with a mass point at $t = \underline{w}$.

3.4 Summary: Theoretical Implications for Estimation

The model delivers four directional predictions that we take to the data, helped by relaxation terms in estimation:

1. Within-firm dispersion. P-firms post a single wage, while M-firms generate within-firm wage dispersion through renegotiation/poaching.
2. $P \to P$ moves. Job-to-job moves between P-firms are associated with wage increases.
3. $P \to M$ moves. Holding the worker's contract value fixed, the wage paid by an M-firm is below the posted wage, implying wage cuts on $P \to M$ transitions.
4. $M \to P$ moves. Workers leave an M-firm only when a posted contract exceeds the firm's retention ceiling $S(p)$, implying the destination posted wage strictly exceeds the origin firm's maximum wage.

In addition, the separation/quit hazard

$$\mathrm{qr}(\theta) = \delta + \kappa\lambda\overline{K}(\theta)$$

links mobility rates to the firm characteristic θ, providing identifying variation for κ.

4 Data

For estimation, we use Austrian matched employer-employee data on the universe of social-security covered employment relationships over the time period 2001-2018. The Arbeitsmarktdatenbank (AMDB) data set is collaboratively produced by the Austrian Labor Market Service and the Federal Ministry for Social Affairs, Health, Care, and Consumer Protection, based on worker-level social security records. A comparable version of this data was previously utilized by Borovickova and Shimer (2017). For each job subject to social security contributions, the data set includes information on start and end dates as well as total annual earnings. Given this information, we construct the daily average wage per job on an annual panel and focus on the employment spell with the highest annual income per worker, following Kline et al. (2020). In addition, the data set contains a limited number of demographic information (gender, age) and firm characteristics (date of first record, location, sector of activity). Using available registers, we can construct an identifier for academic titles, indicating completion of a university degree, and the population density of the workplace.[6]

The sample is composed of workers with ages 25-60 years working at firms that are continuously in operation over the sample period and feature at least 20 workers over the sample period. We also exclude unusual worker histories following Kline et al. (2020)[7] and remove outliers in wages beyond the 2nd and 98th percentile.

5 Identification and Estimation

In the following, we discuss the data generating process (DGP) (Section 5.1) and present a constructive identification argument (Section 5.2). We then show a formal estimation and classification procedure using maximum-likelihood (Section 5.3). Section 5.4 then presents the empirical implementation details of the estimation procedure.

5.1 The DGP

The data consist of firm-level objects and worker histories. There are N firms indexed by j. Each firm has a latent wage-setting type $z_j \in \{P, M\}$ and productivity p_j with type-specific CDFs Γ for M-firms and Γ_P for P-firms. In equilibrium it is convenient to work with a scalar firm characteristic θ_j: for M-firms, θ_j equals the firm's maximal wage (and coincides with productivity), whereas for P-firms θ_j equals the posted wage offer, $\theta_j = q(p_j)$. We denote by Ψ the distribution of θ among P-firms, where $\Psi(\theta) = \Gamma_P \circ q^{-1}(\theta)$.

Firm types are drawn i.i.d.: $z_j = M$ with probability ξ and $z_j = P$ with probability $1 - \xi$. Conditional on z_j, we draw $\theta_j \sim \Gamma$ if $z_j = M$ and $\theta_j \sim \Psi$ if $z_j = P$. The unconditional

[6] We observe that fewer than 5% of the worker population holds an academic degree in the data set, suggesting that data on academic achievements may not be available for all workers. Therefore, we approach this information with caution.

[7] We hence exclude workers who ever worked in the public sector, workers who ever featured more than 10 jobs in a given year, received wages lower than 5 EUR per day and featured extreme wage changes of over 100%.

cross-sectional distribution of firm characteristics is therefore approximately

$$K(\theta) = \xi\Gamma(\theta) + (1-\xi)\Psi(\theta), \qquad \overline{K}(\theta) \equiv 1 - K(\theta).$$

There are I workers indexed by i. In steady state, a worker is unemployed with probability $u = \delta/(\delta+\lambda)$ and employed with probability $1-u = \lambda/(\delta+\lambda)$. Conditional on employment, the steady-state mass of workers employed at a firm with characteristic θ is proportional to

$$\ell(\theta) = \frac{(1-u)I}{N}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^2}.$$

Accordingly, we assign employed workers to firms with probability proportional to $\ell(\theta_j)$. By the law of large numbers $\sum_{j=1}^{N}\ell(\theta_j) \to (1-u)I$. Hence, we draw a match with firm j with a probability proportional to

$$\frac{\ell(\theta_j)}{(1-u)N} = \frac{1}{N}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(\theta_j)\right]^2}.$$

By the law of large numbers

$$\frac{1}{N}\sum_{j=1}^{N}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(\theta_j)\right]^2} \to 1$$

where N gets large.[8]

Worker mobility is as follows. At any time, an employed worker i at a firm j is laid off with probability δ. If not laid off (with probability $1-\delta$) an alternative employer j' is drawn (uniformly) with probability $\kappa\lambda/N$. The probability of not drawing an alternative offer is

$$(1-\delta)\left(1-\kappa\lambda\frac{1}{N}\sum_{1}^{N}\mathbf{1}\{\theta_{j'}>\theta_j\}\right) \simeq 1-\delta-\kappa\lambda\frac{1}{N}\sum_{1}^{N}\mathbf{1}\{\theta_{j'}>\theta_j\} \simeq 1-\delta-\kappa\lambda\overline{K}(\theta_j).$$

Alternatively, a new job offer can be drawn by drawing θ from distribution K and assigning the closest $\theta_{j'}$.

[8] In practice, we can draw θ from the equilibrium distribution $\frac{\delta K(\theta)}{\delta+\kappa\lambda\overline{K}(\theta)}$ and then assign j as the closest θ_j.

5.2 Constructive Identification

We first provide a constructive identification argument in the frictionless benchmark without deviations. We begin by sorting firms into wage-setting types using observable properties of job transitions and wage patterns. Specifically, wage-posting firms (P-firms) exhibit no wage dispersion within the firm. Transitions between P-firms are always associated with wage increases, while transitions from P-firms to M-firms are always associated with wage cuts. Conversely, transitions from M-firms to P-firms involve moving to a wage higher than any wage paid at the origin firm. In the frictionless benchmark, these implications separate types sharply; in the data, we use them as directional restrictions that the likelihood weights rather than imposes exactly.

Using the classification of firms into P-firms and M-firms, we can calculate the market shares n, m, and ξ. Flows into and out of unemployment provide identification of the job destruction rate δ and the job-finding rate for unemployed workers λ. The unemployment rate u is determined by the steady-state relationship:

$$u = \frac{\delta}{\delta + \lambda}.$$

The distribution of θ across P-firms identifies Ψ and across M-firms it identifies Γ. Then, the exit rate from a firm with characteristic θ is given by:

$$\mathrm{qr}(\theta) = \delta + \kappa\lambda\overline{K}(\theta),$$

where $\overline{K}(\theta) = (1-\xi)\overline{\Psi}(\theta) + \xi\overline{\Gamma}(\theta)$. Firm-to-firm transitions thus identify κ. Finally, the productivity p of a P-firm offering wage θ is identified from the first-order condition of profit maximization:

$$\frac{1}{p-\theta} = -2\frac{\mathrm{d}\log\left[\mathrm{qr}(\theta)\right]}{\mathrm{d}\theta}.$$

While the identification algorithm provides a constructive basis for estimation, several practical challenges arise. First, the assumption of no wage dispersion within P-firms must be relaxed, as empirical evidence suggests that wage dispersion is lower, but not absent, in these firms. Second, the model is likely misspecified in certain dimensions, necessitating an estimation approach that introduces slackness in the moment conditions to account for these deviations. To address these concerns, we propose an estimation method that efficiently incorporates all available moments while allowing for flexibility in model predictions. This approach ensures robustness to small misspecifications, reflecting the complexity of real-world labor market dynamics.

5.3 Estimation

A worker trajectory is a sequence $(j_{it}, w_{it}, D_{it})_{t=1}^{T}$, where j_{it} indicates non-employment ($j_{it} = U$) or employment at firm $j_{it} \in \{1, ..., N\}$. Note that our data is conditional on employment. Hence, periods without an employment record are treated as separations governed by a δ-shock. As a consequence, the initial sampling from the stock includes only employed workers, who may subsequently transition into non-employment. The last variable indicates a move: $D_{it} = 0$ (no move), $D_{it} = 1$ (move). Although we write the likelihood for any T, in practice, we will be using two periods: $T = 2$. The population DGP includes unemployment; our estimation sample conditions on being employed at $t = 1$ so the period-1 likelihood is the likelihood of the employed.

The model makes strong predictions about moves which have little chance to hold exactly in the data. We therefore relax the theoretical restrictions but penalize the likelihood for parameter choices that contradict the theoretical predictions. In addition, we simplify the wage dynamics within M-firms as it is impossible to distinguish true wage increases resulting from poaching from measurement error.

Thus, the complete sample likelihood is made of the following contributions.

Firm types. Each firm $j = 1, ..., N$ draws a matching type as a Bernoulli trial: $z_j = M$ with probability ξ and $z_j = P$ with probability $1 - \xi$. Then, conditional on matching type, they draw θ_j from Γ or Ψ. The log-likelihood contribution of firm types is thus

$$\log \mathcal{L}(z_j, \theta_j, \forall j) = \sum_j \mathbf{1}\{z_j = M\} \log [\xi\gamma(\theta_j)] + \mathbf{1}\{z_j = P\} \log [(1-\xi)\psi(\theta_j)] .$$

Then, we proceed to calculate the likelihood of worker trajectories given firms' matching types z_j and productivities θ_j. We generally omit these conditioning variables, unless necessary, to simplify the notations.

Initial worker contribution given firm types. Given the above description of the DGP, we obtain the following initial likelihood contributions:

- If $j_{i1} = j$ and $z_j = P$,

$$\mathcal{L}(j_{i1} = j, w_{i1} \mid z_j = P) = \frac{1}{N} \frac{\delta(\delta + \kappa\lambda)}{\left[\delta + \kappa\lambda \overline{K}(\theta_j)\right]^2} \phi_{\sigma_P}(w_{i1} - \theta_j)$$

  where $\phi_{\sigma_P}(x) = \frac{1}{\sigma_P}\phi(x/\sigma_P)$ allows for a measurement error between the actual wage and the expected one (the firm's wage offer θ_j). In reality, parameter σ_P should not strictly be interpreted as measurement error. This is a way of penalizing classifications that would label all firms as M-firms due to non-zero within-firm variance of wages.

- If $j_{i1} = j$ and $z_j = M$, the theoretical wage is

$$T(t,\theta_j) = t - \int_t^{\theta_j} \frac{\kappa\lambda\xi\overline{\Gamma}(x)\,\mathrm{d}x}{r+\delta+\kappa\lambda(1-\xi)\overline{\Psi}(x)}$$

where t is drawn from distribution $\mathcal{G}(t|\theta) = \left[\frac{\delta+\kappa\lambda\overline{K}(\theta)}{\delta+\kappa\lambda\overline{K}(t)}\right]^2$. Define the probability mass at the lower bound:

$$p_0(\theta) \;\equiv\; \Pr(t = \underline{w} \mid \theta) \;=\; \mathcal{G}(\underline{w} \mid \theta) \;=\; \left[\frac{\delta+\kappa\lambda\,\overline{K}(\theta)}{\delta+\kappa\lambda\,\overline{K}(\underline{w})}\right]^2. \tag{16}$$

$$\mathcal{L}(j_{i1} = j, w_{i1} \mid z_j = M) = \frac{1}{N}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\,\overline{K}(\theta_j)\right]^2}\Bigg[p_0(\theta_j)\,\phi_{\sigma_M}(w_{i1} - T(\underline{w},\theta_j)) + \int_{\underline{w}}^{\theta_j}\phi_{\sigma_M}(w_{i1} - T(t,\theta_j))\; g(t \mid \theta_j)\,dt\Bigg]. \tag{17}$$

where we have used a different measurement error variance σ_M for wages and where

$$g(t \mid \theta_j) = \frac{\mathrm{d}\mathcal{G}(t|\theta_j)}{\mathrm{d}t} = \left[\delta+\kappa\lambda\overline{K}(\theta_j)\right]^2\frac{2\kappa\lambda K'(t)}{\left[\delta+\kappa\lambda\overline{K}(t)\right]^3}.$$

Transition from a posting firm ($j_{it} = j$ and $z_j = P$).

- Unemployment transition:

$$\mathcal{L}(j_{i,t+1} = U \mid j_{it} = j, z_j = P) = \delta.$$

- $P2P$ transition:

$$\mathcal{L}(j_{i,t+1} = j', w_{i,t+1} = w \mid j_{it} = j, z_j = P, z_{j'} = P) = \frac{\kappa\lambda}{N}\Phi_\omega(\theta_{j'} - \theta_j)\phi_{\sigma_P}(w - \theta_{j'}),$$

where $\Phi_\omega(x) = \Phi(x/\sigma_\omega)$ allows for a (small) mobility cost in the transition from j to j'. Here again, parameter σ_ω should not strictly be interpreted as mobility cost. This is a way of giving some slackness to the estimation algorithm by allowing for some transitions to a lower firm type. Parameter σ_ω, like σ_P can be interpreted as a meta-parameter penalizing counterfactual observations. We allow for all types of transitions, but give a negative weight to the ones that contradict the theory.

- $P2M$ transition:

$$\mathcal{L}(j_{i,t+1} = j', w_{i,t+1} = w \mid j_{it} = j, z_j = P, z_{j'} = M) = \frac{\kappa\lambda}{N}\Phi_\omega(\theta_{j'}-\theta_j)\phi_{\sigma_M}(w-T(\theta_j,\theta_{j'})).$$

- No employment transition ($D_{it} = 0$). The worker has not been hit by a layoff shock and has not drawn an alternative firm j' with $\theta_{j'} > \theta_j$. Hence,

$$\mathcal{L}(j_{i,t+1} = j, w_{i,t+1} = w \mid j_{it} = j, z_j = P) = \left[1 - \delta - \frac{\kappa\lambda}{N}\sum_{j'}\Phi_\omega(\theta_{j'} - \theta_j)\right]$$

  Because posted wages are time-invariant and we already use the cross-sectional wage distribution for identification, we set the conditional wage density in the stayer transition to 1 i.e., we use transitions to identify mobility but not wage changes for stayers.

Transition from a matching firm ($j_{it} = j$ and $z_j = M$).

- Unemployment transition:

$$\mathcal{L}(j_{i,t+1} = U \mid j_{it} = j, z_j = M) = \delta.$$

- $M2P$ transition:

$$\mathcal{L}(j_{i,t+1} = j', w_{i,t+1} = w \mid j_{it} = j, z_j = M, z_{j'} = P) = \frac{\kappa\lambda}{N}\Phi_\omega(\theta_{j'} - \theta_j)\phi_{\sigma_P}(w - \theta_{j'}).$$

- $M2M$ transition:

$$\mathcal{L}(j_{i,t+1} = j', w_{i,t+1} = w \mid j_{it} = j, z_j = M, z_{j'} = M) = \frac{\kappa\lambda}{N}\Phi_\omega(\theta_{j'}-\theta_j)\phi_{\sigma_M}(w-T(\theta_j,\theta_{j'})).$$

- No employment transition. In an M-firm, the wage may still increase as a result of poaching. However, we cannot separately identify renegotiation-driven growth from measurement error in wage changes, we exclude the second-period wage level for M-stayers from the transition likelihood and rely on the initial cross-sectional wage distribution for identification of σ_M and firm types z_j.

$$\mathcal{L}(j_{i,t+1} = j, w_{i,t+1} = w \mid j_{it} = j, z_j = M) = \left[1 - \delta - \kappa\lambda \frac{1}{N} \sum_{j'} \Phi_\omega(\theta_{j'} - \theta_j)\right]$$

Overall likelihood objective estimation. The likelihood of a complete sample is

$$\mathcal{L}(z_j, \theta_j, \forall j \;\&\; j_{it}, w_{it}, D_{it}, \forall i, t) = \mathcal{L}(z_j, \theta_j, \forall j) \times \prod_{it} \mathcal{L}(j_{it}, w_{it}, D_{it} \mid z_j, \theta_j, \forall j).$$

The observed sample likelihood is the sum over all possible combinations of firm types:

$$\mathcal{L}(j_{it}, w_{it}, D_{it}, \forall i, t) = \sum_{z_j, \forall j} \left[\mathcal{L}(z_j, \theta_j, \forall j) \times \prod_{it} \mathcal{L}(j_{it}, w_{it}, D_{it} \mid z_j, \theta_j, \forall j)\right].$$

The complete likelihood has a complicated form in terms of the latent variables $z_1, ..., z_N$ as the complete likelihood is not multiplicatively separable with respect to the z_j's. The firm part $\mathcal{L}(z_j, \theta_j, \forall j)$ is separable, but the worker part is not as many workers will exhibit job-to-job transitions involving pairs of unknown firm types. This implies that the workhorse algorithm for estimating discrete mixture models, the EM algorithm, is not applicable because the posterior probability of $z_1, ..., z_N$ given the data is not the product of marginal posterior probabilities and is very difficult to compute. Moreover, in the M-step, we would still have to sum over all possible combinations of $z_1, ..., z_N$, as we do for the likelihood of the observed sample.

Instead we use the following Classification EM algorithm for estimation (see Celeux and Govaert (1992) and Lentz et al. (2023)).

Classification EM The CEM estimation proceeds by the following iterations until convergence.

- **C-step (type update).** Holding parameters Ω and all other firms' types fixed, update each $z_j \in \{P, M\}$ by comparing the complete-data likelihood under $z_j = P$ versus $z_j = M$.

$$\max_{z_1,\ldots,z_N} \mathcal{L}(z_j, \theta_j, \forall j) \times \prod_{it} \mathcal{L}(j_{it}, w_{it}, D_{it} \mid z_j, \theta_j, \forall j)$$

  In practice, we implement the C-step via sequential firm updates (coordinate ascent on the complete-data log-likelihood starting with largest), cycling until no assignment changes.

- **M–step (parameter update).** Update firm parameters Ω_F by maximizing the firm log–likelihood conditional on updated firm types:

$$\max_{\Omega_F} \log \mathcal{L}(z_j, \theta_j, \forall j)$$

We also update parameter estimates for the relative employment mobility κ using the quit rate $\mathrm{qr}(\theta)$.

Note that the remaining labor market parameters λ, δ are estimated outside the CEM estimation procedure as described in section 5.2.

5.4 Empirical Implementation

Information set Estimation and clustering use two periods of data on wages w and firm quality $\theta(z)$ as well as firm IDs j with a total vector of data for estimation $\mathcal{I}$,

$$\mathcal{I} = [w_{i1}, w_{i2}, \theta_{i1}, \theta_{i2}, z_{i1}, z_{i2}, j_{i1}, j_{i2}]$$

with z_{i1}, z_{i2} being latent. Note that firm characteristic θ is assigned over the whole sample period, not only the two years of estimation window.[9]

Parametrization We parametrize the model in the following way: We parametrize the distributions $F \circ S(\theta) := \Psi(\theta)$ and $\Gamma(\theta)$ as Kumaraswamy distributions with parameters $[a_P, b_P, a_M, b_M]$ whose cdf and pdf are given respectively as

$$\mathcal{F}(x|a,b) \quad = 1 - (1 - x^a)^b \quad \mathcal{F}'(x|a,b) \quad = abx^{a-1}(1 - x^a)^{b-1}$$

The two parameters of the Kumaraswamy distribution can be considered as governing the left and right tail of the distribution, respectively. As $x \to 0$, $f(x) \sim x^{a-1}$ and as $x \to 1$, $f(x) \sim (1 - x^a)^{b-1}$. Hence, a controls the left tail and b the right tail of the distribution. Recall that $\theta = p$ for M-firms and $\theta = q(p)$ for P-firms. Given that $\theta \in [\underline{\theta}^D, \overline{\theta}^D]$, $D \in \{P, M\}$ we shift the distribution by $\underline{\theta}^D$ and scale it by $(\overline{\theta}^D - \underline{\theta}^D)$ to preserve the integration limits.

We introduce three hyperparameters—σ_M, σ_P, and σ_ω—which govern the relaxation terms

[9] We initialize firm classifications as a best guess based on within-firm wage variance. We have also tested initialization by random assignment without material changes to the final classification.

ϕ_{σ_M}, ϕ_{σ_P}, and Φ_ω, respectively. The relaxation terms ϕ_{σ_P}, ϕ_{σ_M} and Φ_ω in the likelihood function serve to relax sharp functional restrictions, allowing for deviations between observed wages and mobility choices on the one hand and model predictions on the other hand. Mathematically, these terms enter the likelihood multiplicatively and thus act analogously to regularization penalties used in machine learning, such as those in ridge or Lasso regression (Hoerl and Kennard, 1970; Tibshirani, 1996). Specifically, ϕ_{σ_M} accommodates deviations between observed wages and their model-implied counterparts, while Φ_ω permits worker mobility to firms of lower quality than the origin firm (i.e., $\theta' < \theta$). These components can be interpreted as soft constraints, with the associated parameters σ_M, σ_P and σ_ω controlling the degree of relaxation: smaller values tightly enforce the model's structural predictions, while higher values indicate looser fit and may signal model misspecification. To separately identify the economic parameters and hyperparameters, we implement a sample-splitting strategy, dividing the data into estimation and validation subsets. Economic parameters are estimated on the estimation sample, conditional on a given set of hyperparameters $[\sigma_P, \sigma_M, \sigma_\omega]$. We then determine the hyperparameters by maximizing the out-of-sample log-likelihood within the validation data set, holding fixed the corresponding best-fitting economic parameters. We split worker spells into estimation and validation sets stratified by firm, so each firm appears in both subsamples while keeping worker histories intact. In practice, we construct a coarse grid of hyperparameters by scaling it to the standard deviation of wages and to the standard deviation of job-mover differences in firm characteristics, θ, which constitute the empirical analogues of the relaxation terms.

In addition, we pin down the labor market parameters λ, κ and δ. The total set of parameters to be estimated, Ω, is hence

$$\Omega = [a_P, b_P, a_M, b_M, \lambda, \kappa, \delta, \xi, \sigma_P, \sigma_M, \sigma_\omega]$$

Wage concept for estimation. While our model abstracts from worker heterogeneity, assuming additional worker heterogeneity can be accommodated. In fact, our model is affine in worker quality, as in Flinn and Mullins (2021), such that we can control for unobserved worker quality using a fixed effects specification. Therefore, we present our main results for a specification that nets out worker fixed effects and use the exponentiated residuals in estimation. As a sensitivity check, we also report estimates from a specification that omits worker fixed effects while residualizing for age only. We view these estimates as difficult to interpret because they conflate worker- and firm-level sources of wage variation.

Sample details for estimation. The baseline estimation uses two years of data from 2015 and 2016, consistent with our two-period likelihood setting. Summary statistics for the estimation data set are in table A.10. The data set encompasses around 4700 firms and 620000 workers. There are about 37% of female workers with a typical worker having 42 years of age. We treat the firm characteristic θ_j as time-invariant. To obtain a precise measure of θ_j—and to limit classification noise driven by small firm-year samples—we estimate firm-level θ_j using all observed worker spells at firm j over 2001–2018.

Our estimates are based on a pooled sample of male and female workers to ensure comparability with the German survey data, since the German survey does not allow us to separate firm-level estimates by gender. We argue that Germany and Austria exhibit broadly similar labor market conditions for women, including motherhood penalties of comparable magnitude and high rates of female part-time employment following childbirth as shown in Kleven et al. (2019). For sensitivity, we also report results for a sample with only male workers.

6 Results

Section 6.1 reports our baseline estimates. We estimate that roughly 28% of firms are M-firms in the Austrian data, broadly in line with the 24% share in the German survey. Section 6.2 then uses these estimates to characterize M-firms and to quantify the implications of cross-type mobility. The estimated M-firm profiles are largely consistent with the survey evidence. Mobility from P-firms to M-firms generates a small decline in aggregate output—about 0.01%—but the associated loss is economically meaningful relative to the gains from other worker flows. Finally, counterfactual wage schedules imply that the coexistence of the two firm types lowers average wages relative to a segmented benchmark.

6.1 Estimation Results

Parameter Estimates Online Appendix Table A.11, first row, reports the baseline parameter estimates. In the Austrian sample, 28% of firms are classified as M-firms, compared with 24% of bargaining firms in the German data under our preferred definition. Our estimates for the job-displacement rate ($\delta = 0.02$), the job-finding rate from unemployment ($\lambda = 0.34$) and the relative job-finding rate when employed ($\kappa = 0.18$) lie within the ranges reported in the literature. The hyper-parameters on wage noise σ_M and σ_P are sizable (0.25 and 0.16, respectively), as is the hyper-parameter on mobility ($\sigma_\omega = 1.3$). To set this into perspective, note that the standard deviation of first period wages is 0.20 and the standard deviation of all possible changes in θ for job movers $\theta_{i2} - \theta_{i1}$ is 0.64. Our hyperparameter estimates hence suggest that the model leaves residual dispersion that is absorbed by the deviation terms. Table A.13 assembles the average log-likelihood in the validation sample across the grid of possible hyper-parameters, with the baseline value selected at the one with the highest validation log-likelihood. The table shows that the share of M-firms varies significantly in the chosen hyper-parameters. While changes in the mobility term σ_ω do not have a large impact, we see that increases in the wage noise σ_M and σ_P mostly lead to larger ξ. Higher wage noise makes within-firm dispersion less informative, shifting mass toward the type that rationalizes wage dispersion via bargaining.

As sensitivity checks, Online Appendix Table A.11, rows 2 and 3, report estimates from (i) a specification restricted to male workers and (ii) a specification based on wages that do not net out worker fixed effects. The male-only sample primarily addresses differences in sample composition. The specification without worker fixed effects instead speaks to the source of wage variation used for classification. Our baseline classification relies on within-worker wage changes and therefore separates worker heterogeneity from firm-level wage-setting. When worker fixed effects are omitted, worker heterogeneity is mechanically absorbed into firm components, so the estimated firm-type mixture reflects a different object. We report this alternative both to gauge the quantitative importance of worker heterogeneity for classification and to benchmark the baseline against settings—such as many survey datasets—in which worker fixed effects are unavailable. The male-only specification implies a lower share of M-firms, 18%. In contrast, the residual-wage specification implies a higher share of M-firms, 48%. Together, these results show that the inferred firm-type composition is sensitive to whether worker heterogeneity is purged from wages, underscoring that the interpretation of ξ as the share of M-firms hinges on separating worker and firm components. We view the baseline specification as the closest conceptual match to the German survey analysis. Consistent with this interpretation, the baseline estimates align more closely with the survey's average share of M-firms.

Model Fit We obtain a first look at the baseline estimation results for the firm-type distribution parameters by plotting the estimated firm distributions together with their empirical counterpart. Figure 1 shows the distribution of firm characteristic θ in the empirical data and the estimated $\Gamma(\theta), \Psi(\theta)$ (dashed line) for both firm types. The fitted distributions closely mirror the empirical ones, which is also shown when comparing means and variances of θ by firm type in Online Appendix table A.12.

To further assess model fit, we compare the empirical wage distributions to their model-implied counterparts across estimation periods. We also gauge the role of wage and mobility

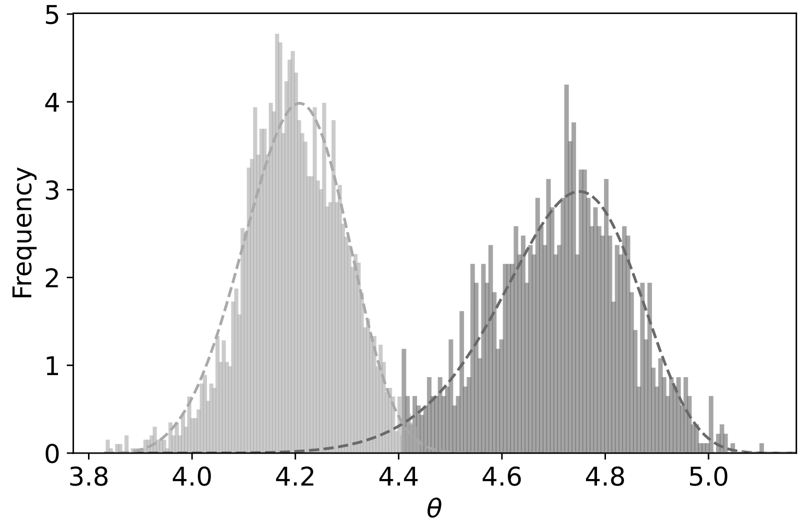


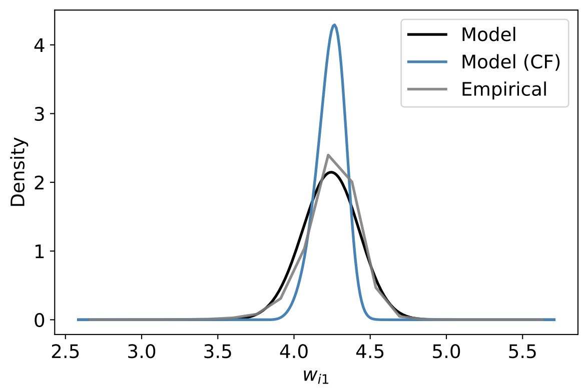
Figure 1: Estimated Distributions of θ

Note: The figure plots the histogram of firm characteristic θ for the observed data (histogram) and the analytical pdfs of the estimated Kumaraswamy distributions $\Gamma(\theta), \Psi(\theta)$ (dashed line) for both firm types.

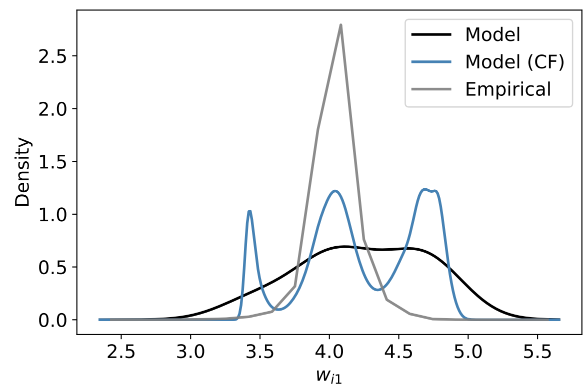
dispersion by contrasting the baseline model with a counterfactual in which the deviation parameters σ_P, σ_M, and σ_ω are set to one-tenth of their estimated values. We focus on two likelihood components. First, Figures 2a and 2b report the initial component. Second, Figures 2c–2d report a dynamic component that captures mobility. Online Appendix Section D.1.1 defines the plotted objects mathematically. In Figures 2a and 2b, we plot the average initial likelihood by w_{i1} bins, together with the corresponding observation counts (Online Appendix equations 18 and 19). We see that the model fits the initial theoretical distributions, in particular for P-firms, and better so than those with lower deviation parameters. For the dynamic likelihood component, we focus on the largest mobility group within each firm type, which is P to P mobility at P-firms and M to P mobility at M-firms. We plot the average likelihood together with the observation count across w_{i2} bins (Online Appendix equations 20 and 21). Figures 2c and 2d show that the likelihood fits well the contribution of movers between P-firm types and for movers to P-firms originating from M-firm types.[10]

Overall, we conclude that the model achieves a good fit to the empirical wage distributions.

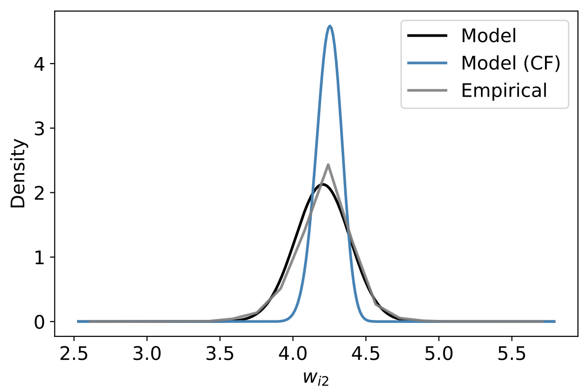
[10]The theoretical M-firm initial wage distribution has a mass-point at the lower bound, $p_0(\theta)$, and a bimodal distribution due to the bi-modality of outside offers in $\bar{K}$. Likewise, the offset of the counterfactual mover densities comes from the mobility term $\Phi_\omega(\theta'-\theta)$: when σ_ω is small it approximates $1\{\theta' > \theta\}$, strongly tilting moves toward higher θ' and shifting w_2 right (especially when σ_P, σ_M are also small), whereas at the estimated ω the term is near 0.5 for typical $\theta' - \theta$, implying little systematic shift.



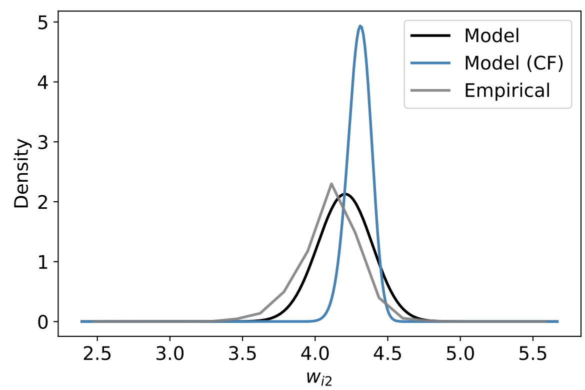
(a) Initial Likelihood: P-firms



(b) Initial Likelihood: M-firms



(c) Dynamic Likelihood: P to P-firm



(d) Dynamic Likelihood: M to P-firm

Figure 2: Workers' wage distributions in periods 1 and 2 by firm types

Note: The figure shows the theoretical log-likelihood components (in black) together with observed empirical counterpart (in gray) and a counterfactual setting with 1/100th of the hyperparameter values (in light blue), for the initial contribution (upper panel), and the dynamic component (lower panel). The empirical counterpart is constructed by binning wages and calculating the corresponding observation count. The likelihood components are defined in Eqs. (18)–(19) (upper panel) and (20)–(21) (lower panel).

To obtain insights into the estimated firm classification, we revert back to section 5 and notably the three characteristic predictions for M-firm identification. Specifically, in the frictionless benchmark without deviations ($\sigma_P = \sigma_M = \sigma_\omega = 0$), three predictions hold: 1) Wage-posting firms exhibit no wage dispersion within the firm, 2) transitions between P-firms are always associated with wage increases 3) while transitions from P-firms to M-firms are always associated with wage cuts. These predictions hold strictly in the presence of no wage noise but to a lesser degree when allowing for model deviations through noise, as we do. In our data, we find that the standard deviation of residualized wages within P-firms is smaller than the standard deviation of wages at M-firms (0.13 and 0.14, respectively). We further find that 69 % of worker transitions from P to P-firm involve wage increases and 28 % of P to M-firm transitions involve a wage cut. We further re-examine the probability of wage cuts upon mobility by type of mobility using the regression framework from the motivation section (see Table 3). Consistent with our findings for Germany, the Austrian data show a coefficient ratio of roughly two for $P2M$ versus MM/PP transitions and confirm that $P2M$

	$\Delta w < 0$	
$P2M$	0.44***	1.84***
	(0.00)	(0.02)
MM/PP	0.17***	0.74***
	(0.00)	(0.01)
Logit	No	Yes
Observations	341601	341601

Table 3: Mobility and Wage Changes

Note: This table shows regression coefficients and p-values in parentheses (with *** $p < 0.01$) for the following regression, where control $x_{i,t}$ is the exit rate $\delta + \lambda\kappa\overline{K}(\theta)$:

$$I\{\Delta w < 0\}_{i,t} = \alpha_{P2M} I\{P2M\} + \alpha_{\text{Firm-Type Stayer}} I\{\text{Firm-Type Stayer}\} + x_{i,t}\beta + \epsilon_{i,t}$$

mobility is significantly associated with wage decreases upon mobility.

Because individual wage changes are noisy and do not fully account for all characteristic firm wage and mobility patterns, within-firm wage variance alone is an imperfect basis for firm classification. We can see that by comparing a plausible initial classification guess, based on a sample split on the within firm variance of wages, and the final firm classification. Relative to the variance-based initialization, the final MLE reassigns 40% of observations and 37% of firms; 77% of these observation-level changes and 61% of firm-level changes are from M to P. Reassignment is concentrated in spells with noisier wage signals (e.g., smaller firms), consistent with within-firm variance being an imperfect sufficient statistic. This can be visually seen in figures A.2b and A.2a in the Online Appendix. The figures plot kernel density estimates of the two log-likelihood differences that enter the firm-type update in the CEM algorithm, separately for firms classified as P or M firms. The right panel reports the difference in workers' log-likelihood contributions at firm j, $d_j^{\text{workers}} \equiv \ell_{j,M}^{\text{workers}} - \ell_{j,P}^{\text{workers}}$, and the left panel reports the difference in firm log-likelihood contributions, $d_j^{\text{firm}} \equiv \ell_{j,M}^{\text{firm}} - \ell_{j,P}^{\text{firm}}$.[11] In both panels, positive values indicate that the data provide relatively stronger support for

[11]For $z \in \{M, P\}$, $\ell_{j,z}^{\text{workers}} = \sum_{it} \log \mathcal{L}(j_{it}, w_{it}, D_{it} \mid z_j = z, \theta_j)$ and $\ell_{j,z}^{\text{firm}} = \log \mathcal{L}(z_j = z, \theta_j)$.

the M-firm model than for the P-firm model, while negative values favor the P-firm model. Accordingly, a rightward shift of the M-firm densities indicates that firms classified as M tend to have higher relative likelihood under the M-firm specification (in that component of the likelihood), as expected under the algorithm. However, the plots also show that some P-firms are not much distinguishable from M-firms. This pattern underscores the need for a comprehensive, likelihood-based classification that accounts for residual wage volatility.

While the parameter estimates and the implied firm classification line up well with the model's qualitative predictions, two auxiliary implications fit the data less well. First, the model overpredicts the share of employment in M-firms. In the model, employment is roughly evenly split across types, with $m/(m+n) = 0.61$ and $n/(m+n) = 0.39$. In the data, by contrast, the corresponding shares are $m_{\text{emp}}/(m_{\text{emp}} + n_{\text{emp}}) = 0.21$ and $n_{\text{emp}}/(m_{\text{emp}} + n_{\text{emp}}) = 0.$.[12] Second, the model fits firm size distributions less well (Online Appendix Figure A.2), a discrepancy that is common in this class of models. Importantly, the framework does not generate type-specific size differences absent additional heterogeneity: conditional on fundamentals, it makes no sharp prediction that M- and P-firms should differ in size. For this reason, departures between the theoretical and empirical size distributions are not unexpected.

6.2 Applications

The estimates allow us to speak to five related questions: (i) what distinguishes M and P firms in the data; (ii) which firms are more productive; (iii) the extent of inefficient mobility and its consequences for aggregate output; (iv) how wages respond to changes in competitive pressures across firm types; and (v) what our findings imply for measurement. We will now discuss these questions in turn.

6.2.1 Characteristics of M and P Firms

Tables 4a and 4b report summary statistics by firm type. Table 4a presents average wages $E[w]$, the variance of wages within firms $Var[w]$ and across firms $Var_j[w]$, the average profit share by firm type $E[\pi/p]$, and the average exit rate $E[qr(\theta)]$.[13] Table 4b reports the average

[12] Here $m = \int \frac{\delta(\delta+\kappa\lambda)}{[\delta+\lambda\kappa\overline{K}(\theta)]^2}\xi\gamma(\theta)d\theta$ and $n = \int \frac{\delta(\delta+\kappa\lambda)}{[\delta+\lambda\kappa\overline{K}(\theta)]^2}(1-\xi)\psi(\theta)d\theta$.

[13] The latter two objects can be computed from our firm estimates. For the exit rate, we have $qr(\theta) = \delta + \lambda\kappa\overline{K}(\theta)$ and for the profit share, for P-firms, $E[\pi/p|z=P] = E[\frac{qr(\theta)}{2\theta\lambda\kappa k(\theta)+qr(\theta)}|z=P]$ and for M-firms $E[\pi/p|z=M] = E[(\theta-w)/p|z=M]$. To see this, notice that the FOC for P-firms implies

$$p(\theta) = \theta + \frac{1}{2}\frac{\delta+\lambda\kappa\overline{K}(\theta)}{\lambda\kappa k(\theta)},$$

and variance of worker age a, the share of workers observed with academic titles, the mean and mode of firm size N, the average population density at the firm location and the average firm age. We find that P-firms, on average, have higher exit rates $qr(\theta)$ and pay higher average wages w than M-firms. Interestingly, while within a given firm type wages and exit rates are negatively correlated—firms with lower exit rates pay higher wages—this pattern does not hold across firm types, as P-firms exhibit both higher wages and higher exit rates than M-firms. This is partly consistent with the evidence from the German survey data in Section 2. As in the German data, P-firms are on average located lower on the job ladder than M-firms, as reflected in their exit rates. In the German context, however, P-firms pay lower total wages on average. Note, however, that the German data do not allow us to control for worker fixed effects, such that those results are not directly comparable to our estimates, which are net of worker fixed effects.[14] As expected, the average variance of wages within firms, $Var[w]$, is larger in M-firms than in P-firms, echoing the larger wage dispersion observed in bargaining firms in the German survey data. The variance of average wages across firms $Var_j[w]$ is however lower at M-firms than at P-firms, reflecting the much larger mass of P-firms with increased scope for heterogeneity.

Average profit shares, $\pi = (p - w)/p$, are lower at P-firms than at M-firms. For both types, expected profit shares rise with productivity, but M-firms exhibit a higher expected profit share even at a given productivity level p. Figure A.3 in the Online Appendix illustrates this pattern by plotting average profit shares on a common productivity support.

Workers differ slightly across firm-types in our data. In the Austrian data, workers at M-firms are slightly older on average, consistent with these firms occupying higher rungs of the job ladder. Based on our measure of academic degrees, P-firms are more skill-intensive. These findings are consistent with our evidence from the German survey data (cf. Table A.4), where P-firms employ a higher share of highly educated workers. P-firms and M-firms also differ systematically in size, age, and location. P-firms tend to be on average larger and older, and they are situated in areas with higher population density on average. The fact that P-firms are on average larger also resonates with the same finding in the German survey data.

Figure 3a provides further detail on sectoral composition across broad sector groups (one-digit industries). Construction and manufacturing contain relatively few bargaining firms,

with $K(\theta) = (1 - \xi)\Psi(\theta) + \xi\Gamma(\theta)$ and $k(\theta) = (1 - \xi)\psi(\theta) + \xi\gamma(\theta)$.

[14] In addition, because M-firms trade off lower entry wages for higher option value, the cross-sectional mean wage can be lower even if productivity/job-ladder rank is higher at M-firms.

	$E[w]$	$Var[w]$	$Var_j[w]$	$E[\pi/p], \%$	$E[qr(\theta)]$
P	4.1972	0.1331	0.0094	7.4367	0.0602
M	4.0125	0.1445	0.0098	13.8570	0.0297

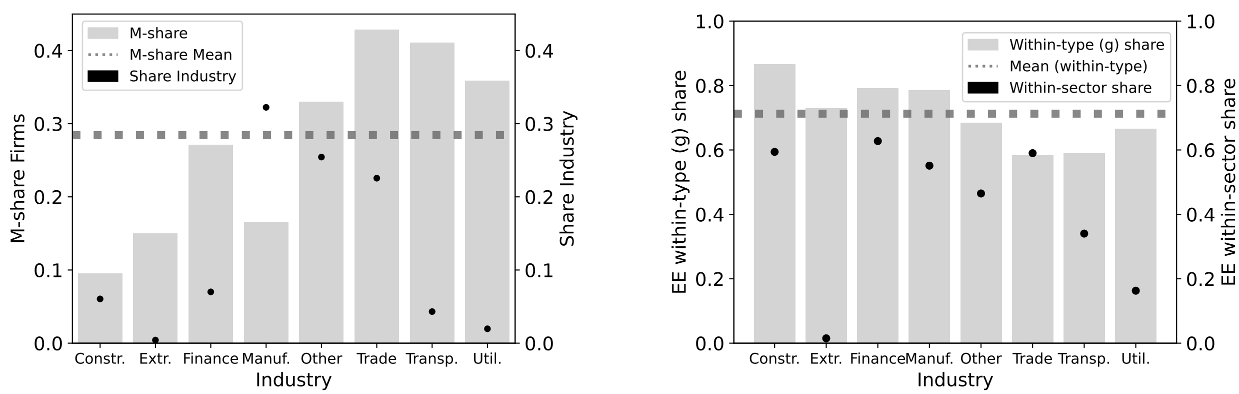
(a) Wages, Profit Share and Firm Exit Rank

	Workers			Firms			
	$E[a]$	$Var[a]$	Acad.	$E[N]$	Mode N	Dens.	F-Age
P	41.541	6.122	0.036	146.852	31	489.224	44.240
M	41.955	6.399	0.015	94.560	31	423.667	39.440

(b) Worker and Firm Characteristics

Table 4: Summary statistics by firm type

Note: The tables show summary statistics by firm type. In the upper panel, $Var[w]$ denotes the within-firm variance of wages, and $Var_j[w]$ denotes the between-firm variance. In the lower panel, N denotes firm size, a denotes worker age, Acad. the average share of workers with academic titles as observed in the data, Dens. denotes average population per km^2. F-Age is firm age.



(a) M-share

(b) Mobility Shares

Figure 3: Firm-Type by Broad Sector

Note: Left - Plotted is the share of M-firms per sector on the left y-axis (histogram) and the share of firms within this sector across the economy on the right axis (dots). The horizontal line represents the average share of M-firms in the economy. Right - Plotted is the share of EE mobility that stays within a firm type on the left y-axis (histogram) and the share of EE mobility staying within the same 1-digit sector on the right axis (dots). The horizontal line represents the average share of firm-type stayers in the economy.

whereas they are more prevalent in service sectors such as finance, trade, and transport. These results also compare to our own results on the German survey data where M-firms where more prevalent among service sector firms. These patterns are reminiscent of Di Addario et al. (2023), who document that the proportion of wage-bargaining firms is highest in the financial sector. At the same time, there is substantial mixing between M- and P-firm types within sectors: the share of M-firms does not exceed 45% in any broad sector group.

Figure 3b sets these results into perspective by examining cross-type worker mobility. We ask whether workers change firm type when they move jobs, or whether the patterns above merely reflect persistent differences in job types. We find some within-type persistence in job-to-job mobility, but only to a limited degree: the probability of remaining in the same firm type largely co-moves with the within-sector staying rate, except in extractive industries, utilities, and transportation. Thus, workers do change firm type when they move jobs in all sectors, indicating that cross-type mobility is an important component of labor reallocation.

6.2.2 Comparing Productivity across Firm Types

We use our estimates to recover and compare the distribution of firm productivity across firm types. Our estimation yields $\Psi(q(p))$, which we use to deduce the P-firm productivity distribution $\Gamma_P(p)$ from two sets of model-implied equilibrium conditions. Specifically, in equilibrium

$$\Gamma_P(p) = \Psi\big(q(p)\big), \qquad \gamma_P(p) = \psi\big(q(p)\big)\, q'(p),$$

where $\psi = \Psi'$ and $\gamma_P = \Gamma'_P$. A second set of constraints follows from the equilibrium wage schedule equation 14 and the first-order condition equation 12. Combining these equilibrium constraints, we back out $\Gamma_P(p)$ as the solution to the following ODE:

$$\Gamma'_P(p) = \frac{(q^0)'(p)\Big\{\delta + \lambda\kappa\Big[(1-\xi)\big(1-\Gamma_P(p)\big) + \xi\Big(\overline{\Gamma}\big(q^0(p)\big) - 2\big[p - q^0(p)\big]\gamma\big(q^0(p)\big)\Big)\Big]\Big\}}{2\lambda\kappa(1-\xi)\,\big[p - q^0(p)\big]}.$$

where $q^0(p)$ is the wage schedule inferred from the FOC and the boundary condition is $\underline{w} = b + \lambda(1-\xi)P(W(\underline{p}))$.

In the baseline, we restrict attention to the monotone part of the productivity–wage schedule to avoid numerical issues at the boundary of the firm distribution. As this necessarily restricts the wage and productivity support of the analysis (specifically, at the lowest considered support w_0, $\bar{K}(w_0) = 0.69$), we also consider as robustness a complementary analysis in which we estimate Ψ subject to the constraint of a positive productivity-wage gradient $p'(q(p)) > 0$. In the following, in sections 6.2.2, 6.2.3 and 6.2.4, we will discuss results for our baseline specification and note changes in our robustness specification. Overall, we find qualitatively robust conclusions across these alternative specifications.

Using our estimates for $\Psi(q(p))$, we undertake two comparisons. First, we ascertain that

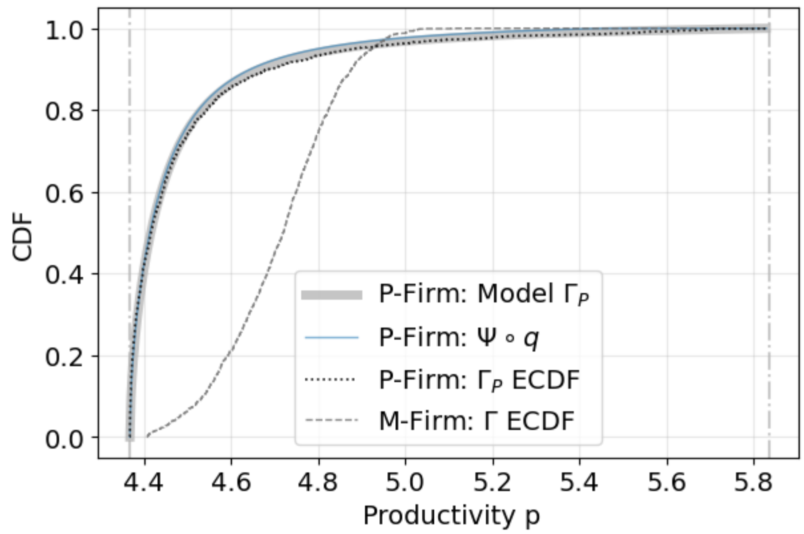


Figure 4: Estimated Distributions of Productivity p

Note: The figure plots the empirical Γ-distribution for M-firms (dashed), together with the backed-out Γ_P distribution for P-firms (calculated - thick gray line - and inferred from the Model's FOC - dotted line) as well as the implied $\Psi(q(p))$ (blue line). All distributions have been rescaled on the truncated monotone productivity-wage schedule.

$\Gamma_P = \Psi(q(p))$. Second, we compare the productivity distribution at P-firms to those at M-firms. Figure 4 presents these comparisons (see Online Appendix Figure A.5 for the robustness specification). The figure shows that we closely match the model-implied identity $\Gamma_P = \Psi(q(p))$. More interestingly, the figure shows that the M-firm productivity distribution places more mass at higher productivity levels than the P-firm distribution. This pattern is consistent with our earlier finding that M-firms occupy higher rungs of the job ladder. These results also persist in the robustness specification. One difference across baseline and robustness specification pertains to the ability to fit the empirical Γ_P, which, by construction, is ascertained in the baseline specification. In the robustness specification, the parameter fit for Ψ aims at maximizing not only the empirical fit but also the additional monotonicity constraint, such that the model cannot achieve the same fit to the data.

6.2.3 Inefficient Mobility

The absence of renegotiation in P firms is a source of inefficient mobility of workers. We quantify the welfare implications of this lack of renegotiation in terms of a) the share of inefficient mobility among E2E movers and b) the loss in output due to this mobility.

Incidence of inefficient mobility Using the estimates of the firm productivity distribution, we analyze the prevalence of inefficient mobility. A worker at firm θ of type P moves inefficiently to an M-firm at rate

$$s(\theta) = \kappa\lambda\xi\left[\Gamma(q^{-1}(\theta)) - \Gamma(\theta)\right]$$

in which case match productivity is less than the former P-firm productivity $q^{-1}(\theta)$ and more than wage θ. The total rate is

$$s = n\int s(\theta)d(G\circ S)(\theta) = (1-u)\int s(\theta)\frac{\delta\left(\delta+\kappa\lambda\right)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^{2}}(1-\xi)\psi(\theta)d\theta.$$

where we average across the distribution of θ across P-workers, $G\circ S$. We set this rate into perspective when comparing to the total flow of moving workers, qr_P, with

$$qr_P = n\kappa\lambda\int \overline{K}(\theta)d(G\circ S)(\theta) = (1-u)\kappa\lambda\int \overline{K}(\theta)\frac{\delta\left(\delta+\kappa\lambda\right)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^{2}}(1-\xi)\psi(\theta)d\theta.$$

and $\bar{K}(\theta(p)) = (1-\xi)\bar{\Psi}(\theta)+\xi\bar{\Gamma}(\theta)$. We calculate the prevalence of inefficient mobility among P-firm moving workers as s/qr_P on the support of the monotone productivity-wage schedule, using the truncated distributions.[15] Given our estimates, we find the value of $s/qr_P = 9.7\%$. Figure A.4 in the Online Appendix illustrates why s/qr_P is relatively modest - when the incidence $s(\theta)$ is small, the exit rate qr_P is high and vice versa.

Output loss We next turn to understanding the welfare implications of inefficient mobility events. The net output loss of workers moving inefficiently is

$$\Delta Q^{-}_{P2M} = (1-u)\kappa\lambda\xi\int\left(\int_{\theta}^{q^{-1}(\theta)}\left(x-q^{-1}(\theta)\right)\gamma(x)dx\right)\frac{\delta\left(\delta+\kappa\lambda\right)(1-\xi)\psi(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^{2}}d\theta$$

The total output at P-firms is

$$Q_P = (1-u)\int q^{-1}(\theta)\frac{\delta\left(\delta+\kappa\lambda\right)(1-\xi)\psi(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^{2}}d\theta$$

and the total output of all firms in the economy is:

$$Q \;=\; Q_P + Q_M = (1-u)\left(\int q^{-1}(\theta)\frac{\delta\left(\delta+\kappa\lambda\right)(1-\xi)\psi(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^{2}}d\theta + \int\theta\frac{\delta\left(\delta+\kappa\lambda\right)\xi\gamma(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^{2}}d\theta\right).$$

[15] We describe the truncation in Online Appendix section D.1.2.

We find that welfare losses from inefficient mobility are small in aggregate: they amount to 0.024% for $\Delta Q^{-}_{P2M}/Q_P$ and 0.009% for $\Delta Q^{-}_{P2M}/Q$. The aggregate loss is small because inefficient moves occur where the productivity gap is limited and because they represent a small share of all separations.

Although the welfare losses are small quantitatively, they are economically meaningful. Notably, the welfare loss due to inefficient mobility ΔQ^{-}_{P2M} is 32% of the welfare gains from workers moving from P to M firms in an upward move ΔQ^{+}_{P2M} and 83% of the welfare gains from workers moving from M to M firms ΔQ_{M2M}. Moreover, because M-firms are higher up on the job ladder, the welfare gains from M to P mobility (ΔQ_{M2P}) are only about one-fiftieth as large as the welfare losses from P to M mobility. We can summarize reallocation on the job also by the sum of absolute output changes across all mobility events ($P2P$, $M2M$, $M2P$, $P2M$) or by the net (signed) sum (cf. Appendix D.1.3 for the corresponding mathematical identities). Under these two aggregations, output losses associated with P to M moves account for 12.6% of total absolute output changes and 16.8% of the net output change generated by job-to-job mobility. Taken together, these findings imply that inefficient mobility is economically meaningful, even though its aggregate welfare effect is numerically small.

In the robustness specification, we find a much larger share of inefficient mobility of $s/qr_P =$ 37%. Despite this larger incidence, we still find relatively small welfare implications of $\Delta Q^{-}_{P2M}/Q_P = 0.05\%$ and $\Delta Q^{-}_{P2M}/Q = 0.02\%$. The economic implications are even more pronounced: Output losses resulting from $P \rightarrow M$ moves account for 36% of the total absolute output changes and 134% of the net output change driven by worker mobility on the job. Interestingly, in the robustness specification, welfare losses due to $P2M$ mobility are larger than welfare gains from $M2P$ mobility, such that cross-type mobility is on average welfare reducing. We find that average welfare losses due to cross-type mobility account for 50% of average welfare gains due to within-type mobility. These larger welfare losses are expected in the robustness exercise - compared to the baseline sample, we add mass to the left of the productivity support, in a region in which mobility across types (from M to P) is largely welfare decreasing.

6.2.4 Wage Effects

Objective and Setting In our framework, wages reflect competitive pressure—through bilateral bargaining at M-firms and profit maximizing wage setting at P-firms. We ask how the coexistence of the two types shapes these pressures. The key primitives are the composition of firm types, ξ, and the type-specific productivity distributions, Γ_M and Γ_P. To quantify counterfactual effects, we vary the parameter vector Ω^C and compute counterfactual average wages for P- and M-firms, $E[q(p)^C]$ and $E[w^C]$, comparing them with the baseline values under the baseline Ω. To do so we first uncover the equilibrium unemployment benefit from our baseline estimates, b. [16] We then compute counterfactual wages on the counterfactual parameter set Ω^C, holding all parameters other than ξ, Γ_M, Γ_P fixed. As before, we focus on the monotone productivity-wage schedule and truncate the distributions accordingly. We summarize impacts as proportional changes regarding the baseline estimates, $E[\Delta w^P \mid z{=}P, \Omega^C, \Omega]$ and $E[\Delta w^M \mid z{=}M, \Omega^C, \Omega]$, with

$$E[\Delta w^P \mid z{=}P, \Omega^C, \Omega] = \frac{E[q(p)^C] - E[q(p)]}{E[q(p)]} \quad E[\Delta w^M \mid z{=}M, \Omega^C, \Omega] \quad = \frac{E[w^C] - E[w]}{E[w]}$$

and report the exact mathematical objects in Online Appendix section D.1.4.

Counterfactual Scenarios and Results We consider four counterfactuals: (i) perfect segmentation - M-firms compete only with M-firms and P-firms only with P-firms (such that $\xi^P = 0$ and $\xi^M = 1$); (ii) a 10 percentage point shift in ξ, consistent with the German survey evidence; (iii) eliminating type-specific heterogeneity by setting $\Gamma_P = \Gamma_M$ (all firms follow the M-type distribution); and (iv) $\Gamma_M = \Gamma_P$ (all firms follow the P-type distribution). Specifically, in the first counterfactual, we shut down cross-type competition by setting the

Scenario	Description	P	M	All
i)	Segmented markets $\xi^P = 0$, $\xi^M = 1$	1.47	8.39	4.62
ii)	Increase in M-Share $\xi + 0.10$	-0.64	10.14	3.40
iii)	Equalizing Dist. to M $\Gamma_P = \Gamma_M$	6.92	-2.90	3.77
iv)	Equalizing Dist. to P $\Gamma_M = \Gamma_P$	1.49	-3.67	-1.88

Table 5: Wage Effects

Note: The table shows percentage changes in average wages by firm type for P-firms, $E[\Delta w^P | z = P, \Omega^C, \Omega]$, and for M-firms, $E[\Delta w^M | z = M, \Omega^C, \Omega]$.

cross-type meeting terms to zero but keep the overall type share ξ fixed. Note that counterfactual results for the whole economy (column 3) are driven by within-type effects and composition effects (for derivation see Online Appendix D.2)

$$E^C_{\text{all}} - E^0_{\text{all}} = \underbrace{\alpha^C\left(E^C_P - E^0_P\right) + \left(1 - \alpha^C\right)\left(E^C_M - E^0_M\right)}_{\text{within-type effect (evaluated at CF weights)}} + \underbrace{\left(\alpha^C - \alpha^0\right)\left(E^0_P - E^0_M\right)}_{\text{composition effect (baseline gap)}} .$$

[16] To do so, we exogenously calibrate the interest rate r to 0.05.

where α^C, α^0 denote counterfactual and baseline firm type shares and $E_P = E[q(p)], E_M = E[w]$ are average wage means by type. As a result, a shift towards more P-firms, which have on average lower wages, lowers economy-wide counterfactual wages through the composition effect.

Results are summarized in Table 5. Under perfect segmentation (scenario (i)), wages increase for both firm types by 1–8%. Removing M-firms from the competitive pool of P-firms shifts competitive pressure toward competition among P-firms, raising wages at P-firms. At M-firms, wage pressure originates from origin firms; because M-firms are more productive, the remaining competitors are on average more productive, which strengthens wage pressure and increases wages at M-firms as well. This scenario illustrates that segmentation can increase wages by intensifying within-type competition.

By contrast, an increase in the share of M-firms has heterogeneous effects (scenario (ii)). Competition at M-firms intensifies, pushing up wages there. However, P-firms now face weaker competitive pressure, as relatively more firms are of type M, so wages at P-firms decline. On average, mean wages increase by about 3.4%. This scenario shows that P-firms benefit from the presence of M-firms, which partially shields them from stronger competition.

When we equalize the firm-type distributions (scenarios (iii) and (iv)), average wages increase or decline. Setting all firms to the (more productive) M-firm distribution (scenario (iii)) mechanically raises wages at P-firms. Yet M-firms now face weaker competitive pressure, which lowers average wages at M-firms. Similarly, when all firms are assigned the P-firm distribution (scenario (iv)), wages mechanically fall at M-firms. At the same time, cross-type competition weakens and within-type competition intensifies, pushing up wages at P-firms.

These results are mostly qualitatively consistent in our robustness specification, with quantitatively larger overall effects and stronger composition effects. These results can be found in Online Appendix table A.14. One notable difference concerns the third scenario, where we find a positive effect for M-firms after equalizing distributions.

Interestingly, wage effects vary over the productivity distribution. M-firms respond to wage pressures if triggered from origin firms. Hence, for instance, scenario 1 has differential effects across the M-firm distribution, with negative effects at lower rungs of the M-firm job ladder. We show this in Online Appendix table A.15 for the robustness specification and in table A.16 for the baseline. The table shows that the unweighted average wage change at M-firms is negative for scenario 1. The positive effect in the weighted specification is driven by the stronger response of firms higher up in the job ladder. These unweighted averages provide a simple reweighting robustness check, since the model does not match the empirical firm-size distribution across types well. Notably, the unweighted effects are smaller and more negative for M-firms, indicating that if employment were less concentrated in high-rung M-firms than implied by the model's size weights, the wage effects would be smaller.

These counterfactual exercises highlight the nontrivial role of competitive pressures for wages across firm types. A natural presumption is that greater market segmentation would weaken wage competition and thereby reduce wage pressure; in our setting, the opposite holds.

6.2.5 Measurement Implications

Our classification bears on several classic questions in labor economics. We highlight two: (i) the sources of wage variability and, (ii) the correlation between firm size and average wages.

Wage variability We decompose the variance of wages for job-movers from the regression for workers at a new job after a job-to-job transition:

$$w_{ijt} = c + \alpha\, p_{j(i,t)} + \beta\, p'_{j(i,t-1)} + \varepsilon_{ijt},$$

where $p_{j(i,t)}$ and $p'_{j(i,t-1)}$ denote destination and origin firm productivities. Table 6a reports the variance shares explained by destination and origin (and their covariance) under five specifications. Column 1 to 3 use the model-consistent productivities, among which column 1 analyzes the full sample with both M and P firms; Columns 2–3 restricts the analysis to P- and M-firms, respectively. Columns 4 and 5 implement a counterfactual in which we map productivity p for the entire sample as if all firms were P- or M-firms, respectively. In this analysis, we use the specification where $p(q)$ is assigned for all firms.

As expected (and by construction), the results indicate that, at P-firms, wage variation is accounted for mostly by destination quality (Column 2), whereas at M-firms it is accounted for mostly by origin quality (Column 3). The whole sample hence yields a mixture of these two scenarios (Column 1). Treating all firms as P-firms (Column 4) or M-firms (Column 5) delivers misleading inferences about the relative roles of origin and destination. These patterns are consistent with the view that the coexistence of firm types rationalizes observed differences in the variance shares attributed to origin and destination firms, as discussed in Di Addario et al. (2023).

Correlation of wages and firm size We previously saw that exit rates and wages correlate positively within firm types but not necessarily across firm types. This invites the question how firm size, a correlate of exit rates in the model, co-varies with firm characteristics θ

	Model-Consistent			Counterfactual	
	All	P	M	All P	All M
Var Destination	0.757	0.875	0.051	0.904	0.827
Var Origin	0.094	0.027	0.923	0.051	0.064
Cov	0.149	0.098	0.026	0.046	0.109

(a) Variance decomposition of wages

Firm characteristic	All	P	M
Average wages - θ^P	0.129	0.119	-0.093
Maximum wages - θ^M	0.500	0.519	0.365

(b) Correlation of log firm size and firm characteristic θ

Note: The panel shows shares of wage variance explained by origin and destination firm productivity and their covariance (upper panel) and the correlation of firm characteristic θ and log firm size (lower panel).

across and within firm types. We correlate log average firm size with firm characteristic θ (Table 6b). A large literature, e.g., Abowd et al. (1999), documents a positive but noisy relationship between firm size and wage components.[17] Because average wages at P-firms are identical to θ, the model predicts a positive size–wage correlation for P-firms, but not necessarily for M-firms. Empirically, Table 6b shows a consistently positive correlation between size and θ, but a weaker and less systematic correlation between size and average wages. We therefore conclude that differences in firm types can account for different findings regarding the correlation of firm sizes and average wages.

7 Conclusion

We develop and estimate a framework with coexistence of wage-posting (P) and wage-bargaining (M) firms, and use an expectation–maximization procedure to classify firms. The estimates align with survey evidence on wage setting at hire: bargaining firms tend to occupy higher rungs of the job ladder and exhibit greater within-firm wage dispersion. They account for 24–28% of firms in our data and set wages in response to competitive pressure from origin firms.

[17] In our model, firm size satisfies $\ell(\theta) = C/\text{qr}(\theta)^2$ with $\text{qr}(\theta) = \delta + \kappa\lambda\overline{K}(\theta)$ and $\overline{K}'(\theta) < 0$ and C being a constant, implying

$$\frac{d}{d\theta} \ln \ell(\theta) = \frac{2\lambda(-\overline{K}'(\theta))}{\delta + \lambda\overline{K}(\theta)} > 0,$$

so log firm size is increasing in θ.

Methodologically, a likelihood-based estimator can recover the two wage-setting regimes in a way that is consistent with theory and external survey benchmarks. This implies that analyses distinguishing firm types are feasible even when survey data are unavailable or limited in scope. Substantively, the coexistence of firm types impacts the economy non-trivially. Although the environment admits inefficient mobility, our estimates imply a small quantitative impact: output is depressed by about 0.01% relative to a setting without such inefficiencies. Yet, these losses are economically meaningful: they amount to 13% to 36% of the output changes generated by job-to-job mobility. Counterfactual analysis indicate that segmenting labor markets would increase average wages at both firms, and that an increase in the share of M-firms by 10 percentage points would on average increase wages. We find that bargaining firms earn higher average profits all else equal. Our estimates also speak to a classic tension in wage-posting models: the homogeneous benchmark implies a decreasing wage density with mass at the lower bound and extreme outcomes at the top. Introducing P/M heterogeneity attenuates, but does not fully resolve, these counterfactual implications.

Our analysis emphasizes firms and their wage-setting regimes. Several extensions appear promising. First, incorporating vacancy data into the estimation and classification could help discipline the model's implications for recruiting behavior. A natural next step would be to embed the framework in general equilibrium with endogenous vacancy posting, which would allow firms' choices between wage bargaining and wage posting to be rationalized as equilibrium outcomes. Our findings on average profits across types can guide the modeling choices underlying such extensions. Second, longer worker panels could be used to study richer wage dynamics, for example by allowing for tenure contracts at wage-posting firms in the spirit of Burdett and Coles (2003). Finally, it would be useful to examine how wage-setting practices in M- and P-firms shape gender wage gaps, building on Card et al. (2015).

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Online Appendices

A Notation

Table A.1: Notations (by order of appearance)

Object	Notation	Property	EqRef
Firm productivity	p		
Fraction of matching firms	ξ		
Fraction of posting firms	$1-\xi$		
Distribution of matching firms' productivities	$\Gamma(p)$	$\gamma = \Gamma'$	
Support of firm productivities	$[\underline{p}, \overline{p}]$		
Present value of a job contract	W		
Distribution of posting firms' value offers	$F(W)$	$f = F'$	
Support of contract values (equilibrium)	$[\underline{W}, \overline{W}]$	$\underline{W} \geq V_0$	
Flow value of unemployment	b		
Time discount rate	r		
Present value of unemployment	V_0		
Option value of search	$P(W)$	$P(W) = \int_W^{\overline{W}} \overline{F}$	(1)
Job offer arrival rate	λ		
Layoff rate	δ		
Maximal value of a job in matching firm	$S(p)$	$S(\underline{p}) \geq V_0$	(4)
Current wage	w		
Wage function for posting firms	$w_P(W)$	$w_P = S^{-1}$	(3)
Wage function for matching firms	$w_M(W,p)$		(3.1)
Wage link function	$T(w,p)$	$w_M = T(w_P, p)$	(5)
Fraction of unemployed	u		
Fraction employed at posting firms	n		
Fraction employed at matching firms	m		
Distribution of values in posting labor force	$G(W)$	$g = G'$	(9)
Distribution of values in matching labor force	$L(p)$	$l = L'$	(8)
Aggregate distribution of offered values	$K(W)$	$K = (1-\xi)F \circ S + \xi\Gamma$	(7)
Equilibrium profit of posting firms	$\pi(p)$		
Equilibrium wage offer	$q(p)$		(13)
Distribution of contracts in matching firms	$G(t\|p)$		(15)

B German Data Sources

For our empirical motivation, we use the datasets IABSE, the business panel BHP and the matched data set IABSE-ADIAB, which contains the labor market history of workers who could be matched to the IABSE survey. In addition to all these data sets, we use the information on vacancies and last hires from the JVS. Note that at the time of analysis, the IABSE-ADIAB could not be merged to the BHP dataset.

The IABSE-ADIAB links administrative employment records with survey data, enabling analysis of labor market trajectories alongside rich socio-economic survey responses such as education, location or age. The IABSE dataset contains purely administrative longitudinal data, capturing employment biographies, unemployment spells, and social security status for a large sample of individuals. Finally, the BHP (Establishment History Panel) focuses on firm-level data, detailing employment dynamics within establishments, with variables on employee counts, industry, and location. The Job Vacancy Survey (JVS) provides detailed, establishment-level data on job vacancies in Germany. This dataset captures both filled and unfilled job vacancies across different sectors, as well as employer-reported information on hiring difficulties, recruitment channels, and reasons for vacancies.

C Additional German Data Information

	2011	2012	2013	2016	2017	2018	2019
Female Share	0.42	0.42	0.44	0.45	0.45	0.43	0.43
Size	316.09	380.96	298.38	442.60	261.69	354.20	283.51
Age	39.96	39.93	39.98	40.73	40.97	41.23	41.22
Spread Wages	0.34	0.32	0.31	0.32	0.31	0.31	0.30
Wage	4.42	4.45	4.45	4.52	4.53	4.57	4.60
25 Percentile	4.20	4.24	4.25	4.31	4.33	4.37	4.40
75 Percentile	4.54	4.56	4.56	4.62	4.64	4.68	4.71
Poachingrank	0.51	0.51	0.52	0.51	0.51	0.52	0.52
Exitranking	0.41	0.40	0.40	0.39	0.38	0.37	0.35
Manufacturing	0.15	0.15	0.13	0.13	0.15	0.16	0.13
Services	0.55	0.52	0.55	0.53	0.53	0.53	0.54
East	0.18	0.19	0.19	0.18	0.20	0.19	0.20
Coll.Agreem.	0.58	0.56	0.63	0.58	0.57	0.53	0.54
Pay More	0.11	0.11	0.14	0.13	0.15	0.19	0.19
Bargaining	0.37	0.35	0.40	0.42	0.45	0.48	0.47
Bargaining +	0.19	0.19	0.21	0.22	0.25	0.29	0.30
# Firms	8987	8167	8710	7232	8968	8792	8567

Table A.2: Summary Statistics

Note: The table contains summary statistics across time. Wage spread denotes the difference between the 75th and the 25th percentile of log wages. "Bargaining" refers to question 1, whereas "Bargaining+" refers to our preferred classification using both questions 1 and 2. All statistics are weighted using survey weights.

	Average
Number Firms	24793
Female Share	0.41
FirmSize	2.97
Age	33.42
Barg. Firm	0.08
Barg. Firm +	0.05
Variance Wages	0.55
Variance Entry Wages	0.48
Log Wage	4.00
High School	0.52
East	0.55
Temp.Contract	0.36
Part-time	0.20
Manufacturing	0.07
Services	0.09
Pay More	0.12
Coll.Agreem.	0.58
Other Ren.	0.05
$E[w_{-1}]$	3.86
$M2P$	0.06
MM/PP	0.86
$P2M$	0.08
Mover	1.00
$\Delta w < 0$	0.33
High Ed.	0.03
Median Sect.	13.00
Bargaining +	0.22

Table A.3: Summary Statistics for JVS and worker panel data: sample of movers

Note: $E[w_{-1}]$ denotes the average observed coworker wage. "Bargaining" refers to question 1, whereas "Bargaining+" refers to our preferred classification using both questions 1 and 2. "Bargaining Firm" denotes the classification of firms into either type. High Education refers to at least "Abitur".

	All	M	P
Barg. Firm +	0.04	1.00	0.00
Female Share	0.44	0.40	0.46
Age	33.34	37.10	33.20
Variance Wages	0.43	0.45	0.43
Variance Entry Wages	0.31	0.36	0.31
Log Wage	3.68	4.12	3.66
High School	0.56	0.75	0.56
East	0.50	0.48	0.50
Temp.Contract	0.26	0.19	0.27
Part-time	0.27	0.20	0.27
Manufacturing	0.04	0.31	0.03
Services	0.06	0.42	0.05
Pay More	0.14	0.29	0.09
Coll.Agreem.	0.47	0.00	0.62
Other Ren.	0.01	0.06	0.01
$E[w_{-1}]$	3.74	4.08	3.73
$M2P$	0.01	0.00	0.01
MM/PP	0.31	0.01	0.32
$P2M$	0.02	0.29	0.01
Mover	0.35	0.30	0.35
$\Delta w < 0$	0.15	0.11	0.15
High Ed.	0.02	0.01	0.02
# Firms	326394	8274	318120
# Obs. per Firm	2.61	2.38	2.61

Table A.4: Summary Statistics for JVS and worker panel data: firm averages

Note: $E[w_{-1}]$ denotes the average observed coworker wage. "Bargaining" refers to question 1, whereas "Bargaining+" refers to our preferred classification using both questions 1 and 2. "Bargaining Firm" denotes the classification of firms into either type. High Education refers to at least "Abitur".

	(1)	(2)	(3)	(4)	(5)	(6)
MM	0.0658	0.0831^{+}	0.0792^{+}	0.0783^{+}	0.361^{+}	0.362^{+}
	(0.145)	(0.060)	(0.072)	(0.076)	(0.076)	(0.075)
PP	0.0216^{+}	0.0525*	0.0582*	0.0591*	0.281*	0.282*
	(0.098)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$P2M$	0.0527*	0.103*	0.101*	0.1000*	0.473*	0.475*
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	38806	38806	38806	38806	38806	38806
Controls		+Firm Q.	+Demo	+Year	Logit	+ Other Ren.

p-values in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$

Table A.5: Probability Wage Decrease Upon Mobility based on Mobility Type

Note: The table contains regression coefficients of the probability of wage decreases upon mobility on the type of mobility. We choose the $M2P$ mobility as our baseline contrast. Columns 1-4 present coefficients in a linear probability model whereas columns 5-6 show results for a logit model. "Demo" refers to demographics education, gender, age, firm location (east/west). "Other Ren" refers to the offer of other remunerations.

	(1)	(2)	(3)	(4)	(5)	(6)
MM/PP	-0.0274*	0.00203	0.00683	0.00681	0.0374	0.0399
	(0.007)	(0.841)	(0.498)	(0.501)	(0.427)	(0.398)
$P2M$	-0.0111	0.0350*	0.0342*	0.0334*	0.163*	0.172*
	(0.396)	(0.007)	(0.008)	(0.009)	(0.007)	(0.005)
Observations	38853	38853	38853	38853	38853	38853
Controls		+Firm Q.	+Demo	+Year	Logit	+ Other Rem.

p-values in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$

Table A.6: Probability Wage Decrease Upon Mobility based on Mobility Type

Note: The table contains regression coefficients of the probability of wage decreases upon mobility on the type of mobility. We choose the $M2P$ mobility as our baseline contrast. Columns 1-4 present coefficients in a linear probability model whereas columns 5-6 show results for a logit model. "Demo" refers to demographics education, gender, age, firm location (east/west). "Other Ren" refers to the offer of other remunerations. In this table, we define bargaining firms using question 1 only.

C.1 Further Indications for Wage Posting/Wage Bargaining

	(1) Stayer Wage Growth	(2) Stayer Wage Growth
M-firm	-0.00654*	0.00572*
	(0.004)	(0.013)
Controls	0	1
Observations	813926	813926

p-values in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$

Table A.7: Wage Growth of Job Stayers

Note: The table contains regression coefficients of stayer wage growth on firm type and control variables (in column 2) for education, gender, age, firm location (east/west) and year.

	N	Mean firm-level SD Res. Wages
P-firm	225956	0.2884
M-firm	11024	0.3030

Table A.8: Standard Deviation Residual Wages

Note: The table contains the standard deviation of residual wages by firm type.

	(1)	(2)	(3)	(4)
Average Res.-Wage	-0.157*	-0.154*		
	(0.000)	(0.000)		
M-firm	-0.0758*	-0.0854*	-0.120*	-0.130*
	(0.000)	(0.000)	(0.000)	(0.000)
M-firm × Average Res.-Wage	0.0212*	0.0194*		
	(0.000)	(0.000)		
Average Res.-Wage Rank			-0.000000187*	-0.000000187*
			(0.000)	(0.000)
M-firm × Average Res.-Wage Rank			5.16e-08*	5.18e-08*
			(0.000)	(0.000)
Observations	1204468	1204468	1204468	1204468
Controls	No	Yes	No	Yes

p-values in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$

Table A.9: Separation Rate and Firm Wage Rank

Note: The table contains regression coefficients of worker separations on the firm residual average wage (columns 1 and 2) and the wage rank (columns 3 and 4). Columns 2 and 4 further add control variables for education, gender, age, firm location (east/west) and year. Reading: The negative correlation of firms' wage rank with workers' separation is weaker at M-firms.

D Further Results

D.1 Additional Mathematical Details for Results Section

D.1.1 Estimation Examination

Specifically, for P-firms we plot

$$(1-u)\int \frac{(1-\xi)\psi(\theta_j)}{n}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(\theta_j)\right]^2}\phi_{\sigma_P}(w_{i1}-\theta_j)\,\mathrm{d}\theta_j \tag{18}$$

and for M-firms

$$(1-u)\int \frac{\xi\gamma(\theta_j)}{m}\frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\,\overline{K}(\theta)\right]^2}\left[p_0(\theta_j)\,\phi_{\sigma_M}\big(w_{i1}-T(\underline{w},\theta_j)\big)+\int_{\underline{w}}^{\theta}\phi_{\sigma_M}\big(w_{i1}-T(t,\theta_j)\big)\,g(t\mid\theta)\,dt\right]d\theta_j \tag{19}$$

Specifically, for P to P mobility we plot

$$\int \frac{N}{n}\ell_P(\theta)\int(1-\xi)\psi(\theta')\Phi_\omega(\theta'-\theta)\phi_{\sigma_P}(w_2-\theta')d\theta' d\theta, \tag{20}$$

with

$$\ell_P(\theta)=\frac{m+n}{N}\frac{\delta(\delta+\lambda\kappa)}{\left[\delta+\lambda\kappa\overline{K}(\theta)\right]^2}(1-\xi)\psi(\theta).$$

and for M to P mobility

$$\int \frac{N}{m}\ell_M(\theta)\int(1-\xi)\psi(\theta')\Phi_\omega(\theta'-\theta)\phi_{\sigma_P}(w_2-\theta')d\theta' d\theta. \tag{21}$$

with

$$\ell_M(\theta)=\frac{m+n}{N}\frac{\delta(\delta+\lambda\kappa)}{\left[\delta+\lambda\kappa\overline{K}(\theta)\right]^2}\xi\gamma(\theta).$$

D.1.2 Truncation

Let p_1 be the truncation point in productivity space and $\theta_1 \equiv q(p_1)$ in wage space. We adjust the distributions for truncation as follows, where we show truncation for P firm distributions, with M firm distributions treated equivalently. Define the normalizing constants

$$Z_P \equiv 1-\Gamma_P(p_1), \qquad Z_\Psi \equiv 1-\Psi(\theta_1).$$

The truncated (conditional) CDFs on $[p_1, p_H]$ and $[\theta_1, w_H]$ are

$$\Gamma_P^\dagger(p) \;=\; \frac{\Gamma_P(p)-\Gamma_P(p_1)}{Z_P}, \quad p\in[p_1,p_H], \qquad \Psi^\dagger(\theta) \;=\; \frac{\Psi(\theta)-\Psi(\theta_1)}{Z_\Psi}, \quad \theta\in[\theta_1,w_H].$$

Their densities are

$$\gamma_P^\dagger(p) \;=\; \frac{\gamma_P(p)}{Z_P}\,\mathbf{1}\{p\in[p_1,p_H]\}, \qquad \psi^\dagger(\theta) \;=\; \frac{\psi(\theta)}{Z_\Psi}\,\mathbf{1}\{\theta\in[\theta_1,w_H]\}.$$

D.1.3 Output Changes due to Job-to-Job Mobility

Remaining output flows due to worker mobility on the job are

$$\Delta Q^+_{P2M} = (1-u)\kappa\lambda\xi \int \left(\int_{q^{-1}(\theta)}^{\infty} \left(x - q^{-1}(\theta)\right)\gamma(x)dx\right) \frac{\delta\left(\delta+\kappa\lambda\right)(1-\xi)\psi(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^2} d\theta,$$

$$\Delta Q_{M2P} = (1-u)\kappa\lambda(1-\xi) \int \left(\int_{\theta}^{\infty} \left(q^{-1}(x) - \theta\right)\psi(x)dx\right) \frac{\delta\left(\delta+\kappa\lambda\right)\xi\gamma(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^2} d\theta,$$

$$\Delta Q_{P2P} = (1-u)\kappa\lambda(1-\xi) \int \left(\int_{q^{-1}(\theta)}^{\infty} \left(q^{-1}(x) - q^{-1}(\theta)\right)\psi(x)dx\right) \frac{\delta\left(\delta+\kappa\lambda\right)(1-\xi)\psi(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^2} d\theta,$$

$$\Delta Q_{M2M} = (1-u)\kappa\lambda\xi \int \left(\int_{\theta}^{\infty} (x-\theta)\,\gamma(x)dx\right) \frac{\delta\left(\delta+\kappa\lambda\right)\xi\gamma(\theta)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^2} d\theta,$$

D.1.4 Counterfactual Calculations

We compute counterfactual expected wages as

$$E[q(p)^C] = \int q(p)^C\, g_P^C(p)\, dp, \tag{22}$$

$$g_P^C(p) = \frac{\delta(\delta+\kappa\lambda)(1-\xi^C)\,\psi^C\big(q(p)^C\big)}{\left[\delta+\kappa\lambda\,\overline{K}^C(p)\right]^2}$$

$$E[w^C] = \int \left[p_0^C(p)\,T^C(\underline{w}^C, p) + \int_{\underline{w}^C}^{p} T^C(t,p)\,g^C(t\mid p)\,dt\right] g_M^C(p)\,dp \tag{23}$$

$$g_M^C(p) = \frac{\delta(\delta+\kappa\lambda)\xi^C\,\gamma^C(p)}{\left[\delta+\kappa\lambda\,\overline{K}^C(p)\right]^2},$$

with

$$\psi^C\big(q(p)^C\big) = \frac{\gamma_P(p)}{\big(q^C\big)'(p)},$$
$$\overline{K}^C(p) = (1-\xi^C)\,\Psi^C\big(q(p)^C\big) + \xi^C\,\Gamma^C(p),$$
$$K'^C(p) = (1-\xi^C)\,\psi^C\big(q(p)^C\big) + \xi^C\,\gamma^C(p).$$

Using

$$\underline{w} = b + (1-\kappa)\lambda(1-\xi)\int_{\underline{w}}^{\overline{w}} \frac{\overline{\Psi}(w)dw}{r+\delta+\kappa\lambda(1-\xi)\overline{\Psi}(w)},$$

we calibrate b from parameter estimates. For a given counterfactual parameter vector, the equilibrium wage schedule $q(p;\theta)$ solves the ODE

$$q'(p) = \frac{2\big[p-q(p)\big]\lambda\kappa(1-\xi)\gamma_P(p)}{\delta+\lambda\kappa\Big[(1-\xi)\overline{\Gamma}_P(p)+\xi\big(\overline{\Gamma}(q(p))-2\big[p-q(p)\big]\gamma(q(p))\big)\Big]}, \tag{24}$$

with the boundary condition $\underline{w} = b + \lambda(1-\xi)P(W(\underline{p}))$

$$P\big(W(\underline{p})\big) = \int_{\underline{p}}^{\bar{p}} \frac{\big(1-\Gamma_P(x)\big)\,q'(x)}{(r+\delta)+\kappa\lambda(1-\xi)\big(1-\Gamma_P(x)\big)}\,dx. \tag{25}$$

D.2 Aggregation and decomposition

Let $g_P(p)$ denote the density over p used for the P-side aggregation, and let $g_M(\theta)$ denote the corresponding density over θ used for the M-side aggregation. Define the masses

$$SP := \int g_P(p)\,dp, \qquad SM := \int g_M(\theta)\,d\theta,$$

and the associated mass-weighted totals

$$EP := \int q(p)\,g_P(p)\,dp, \qquad EW := \int w(\theta)\,g_M(\theta)\,d\theta,$$

so that the within-type means are $E_P := EP/SP$ and $E_M := EW/SM$. The overall mean is the pooled, mass-weighted mean

$$E_{\text{all}} := \frac{EP+EW}{SP+SM} = \frac{SP\,E_P + SM\,E_M}{SP+SM} = \alpha E_P + (1-\alpha)E_M, \qquad \alpha := \frac{SP}{SP+SM}.$$

For a counterfactual C relative to baseline 0, write α^C, α^0 and (E_P^C, E_M^C), (E_P^0, E_M^0). Then

$$E_{\text{all}}^C - E_{\text{all}}^0 = \alpha^C E_P^C + (1-\alpha^C)E_M^C - \alpha^0 E_P^0 - (1-\alpha^0)E_M^0,$$

which can be rearranged as the exact two-term decomposition

$$E_{\text{all}}^C - E_{\text{all}}^0 = \underbrace{\alpha^C\big(E_P^C - E_P^0\big) + \big(1-\alpha^C\big)\big(E_M^C - E_M^0\big)}_{\text{within-type effect (evaluated at CF weights)}} + \underbrace{\big(\alpha^C - \alpha^0\big)\big(E_P^0 - E_M^0\big)}_{\text{composition effect (baseline gap)}}.$$

D.3 Further Estimation Results

Workers (N)	621825
Firms (N)	4678
Female share (Mean)	0.367
Female share (Sd)	0.482
Age (Mean)	42.246
Age (Sd)	9.918
Log-Wage (Mean)	4.206
Log-Wage (Sd)	0.192

Table A.10: Summary Statistics Estimation Sample

Estimated Parameters								Hyper-Parameters		
ξ	δ	λ	κ	a_P	b_P	a_M	b_M	σ_M	σ_P	σ_ω
Baseline										
0.284	0.021	0.338	0.182	4.236	693.911	7.506	192.563	0.254	0.160	1.292
Male Only										
0.177	0.014	0.235	0.278	2.696	67.865	26.072	521201.140	0.331	0.208	1.009
No FE										
0.478	0.020	0.333	0.185	6.365	510.937	16.347	6.082	0.190	0.301	1.399

Table A.11: Parameter Estimates

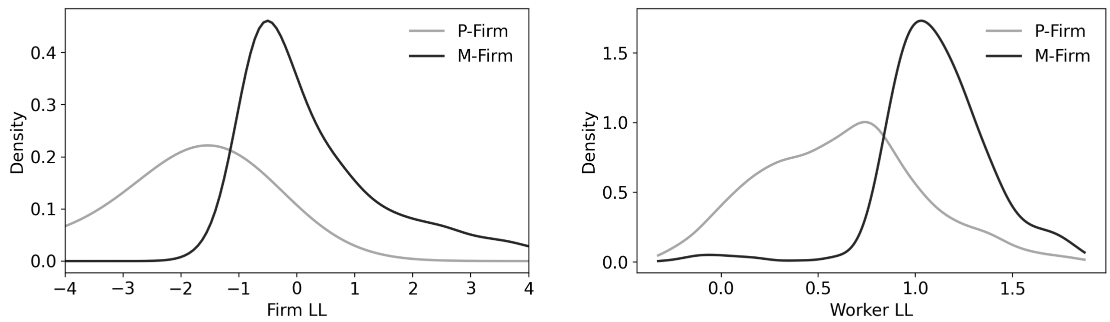
	Mean		Variance	
	Fitted	Empirical	Fitted	Empirical
M	4.7100	4.7111	0.0191	0.0171
P	4.1965	4.1972	0.0096	0.0094

Table A.12: Distribution Comparison

σ_P	σ_M	σ_ω	ξ (%)	Avg. ll
0.1008	0.1008	0.3231	33.0	-8.864
0.1008	0.1008	0.5129	33.0	-8.857
0.1008	0.1008	0.8141	33.0	-8.854
0.1008	0.1008	1.2924	33.0	-8.853
0.1008	0.1600	0.3231	32.0	-8.856
0.1008	0.1600	0.5129	32.0	-8.847
0.1008	0.1600	0.8141	32.0	-8.844
0.1008	0.1600	1.2924	32.0	-8.844
0.1600	0.1008	0.3231	33.0	-8.854
0.1600	0.1008	0.5129	33.0	-8.847
0.1600	0.1008	0.8141	33.0	-8.844
0.1600	0.1008	1.2924	33.0	-8.843
0.1600	0.1600	0.3231	33.0	-8.870
0.1600	0.1600	0.5129	33.0	-8.862
0.1600	0.1600	0.8141	33.0	-8.859
0.1600	0.1600	1.2924	33.0	-8.857
0.1600	0.2541	0.3231	28.0	-8.811
0.1600	0.2541	0.5129	28.0	-8.805
0.1600	0.2541	0.8141	28.0	-8.800
0.1600	0.2541	1.2924	28.0	-8.799
0.2541	0.1600	0.3231	40.0	-9.190
0.2541	0.1600	0.5129	40.0	-9.183
0.2541	0.1600	0.8141	40.0	-9.180
0.2541	0.1600	1.2924	40.0	-9.178
0.2541	0.2541	0.3231	41.0	-9.208
0.2541	0.2541	0.5129	41.0	-9.200
0.2541	0.2541	0.8141	41.0	-9.197
0.2541	0.2541	1.2924	41.0	-9.195
0.2541	0.4033	0.3231	40.0	-9.180
0.2541	0.4033	0.5129	40.0	-9.170
0.2541	0.4033	0.8141	40.0	-9.167
0.2541	0.4033	1.2924	40.0	-9.165
0.4033	0.2541	0.3231	64.0	-9.862
0.4033	0.2541	0.5129	64.0	-9.853
0.4033	0.2541	0.8141	64.0	-9.846
0.4033	0.2541	1.2924	64.0	-9.844
0.4033	0.4033	0.3231	34.0	-9.368
0.4033	0.4033	0.5129	37.0	-9.395
0.4033	0.4033	0.8141	38.0	-9.406
0.4033	0.4033	1.2924	38.0	-9.405

Table A.13: Hyper-Parameter Estimation Results

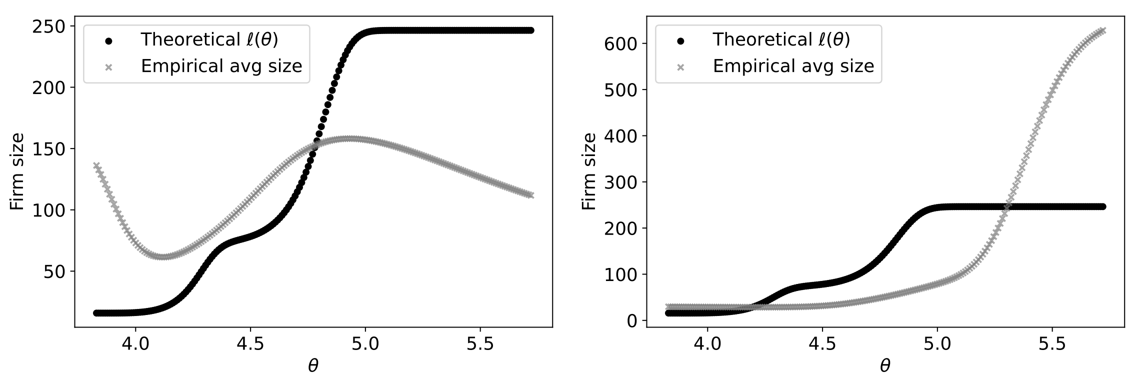
Note: Validation average log-likelihood (ll) and share of matching firms for each grid point during hyper-parameter search. For comparison, the standard deviation of first period wages is 0.20 and the standard deviation of all possible changes in θ for job movers $\theta_{i2} - \theta_{i1}$ is 0.64.



(a) Relative Firm Likelihood (b) Relative Worker Likelihood

Figure A.1: Clustering - Likelihood Components

Note: The figures plot kernel density estimates of the two log-likelihood differences that enter the firm-type update in the CEM algorithm, separately for firms classified as P and M-firms. See main text for details.



(a) P-Firms (b) M-Firms

Figure A.2: Firm Size Distribution in Theory and Data

Note: The figures plot the theoretical and empirical distribution of average firm size $\ell(\theta) = \frac{I}{N} \frac{\delta(\delta+\kappa\lambda)}{\left[\delta+\kappa\lambda\overline{K}(\theta)\right]^2}$.

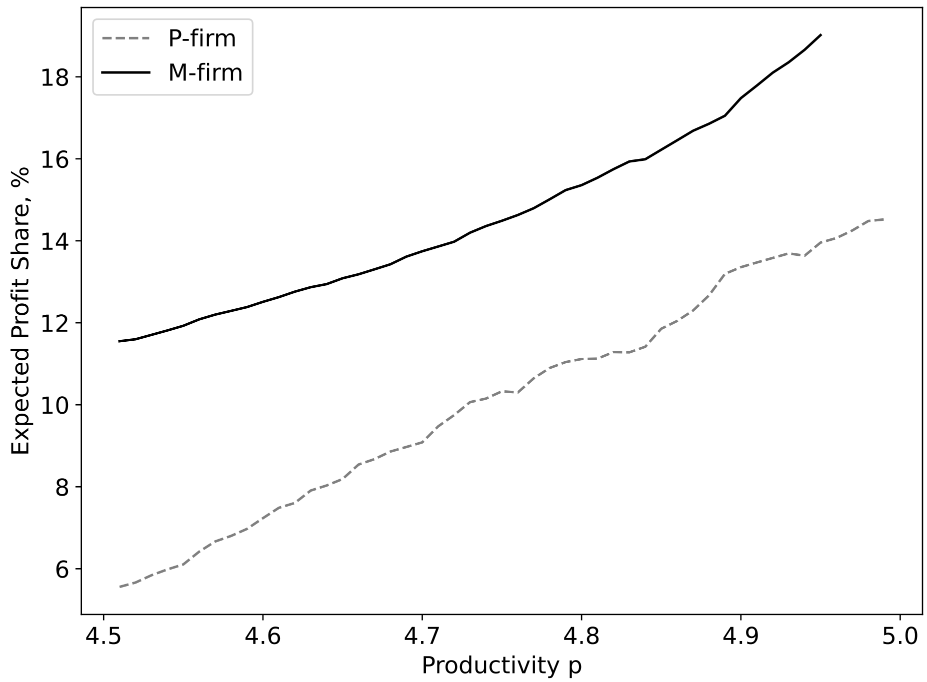


Figure A.3: Expected Profits by Firm-Type

Note: Plotted is the expected profit share per firm type, for M-firms (right) and P-firms (left) respectively.

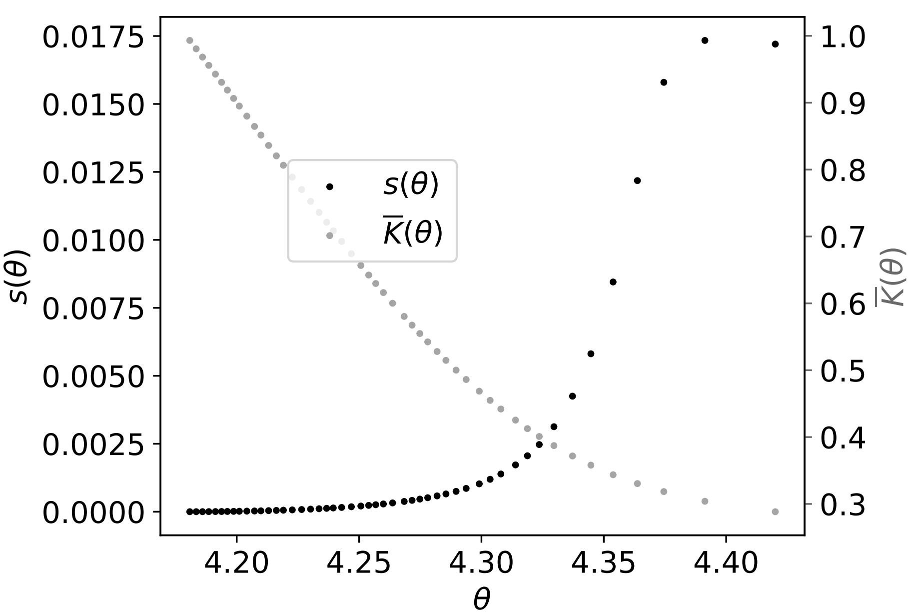


Figure A.4: Calculation Incidence Inefficient Mobility

Note: Plotted is the incidence of inefficient mobility $s(\theta)$ (left axis) and of firm exits $K(\theta)$ (right axis) (see text for details).

D.4 Alternative Wage-Productivity Schedule

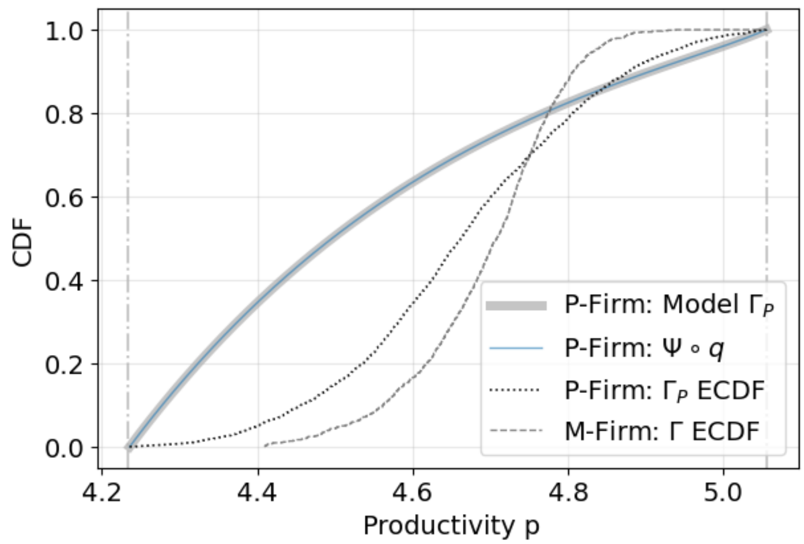


Figure A.5: Estimated Distributions of Productivity p in the Robustness Specification

Note: The figure plots the empirical Γ-distribution for M-firms (dashed), together with the backed-out Γ_P distribution for P-firms (calculated - thick gray line - and inferred from the Model's FOC - dotted line) as well as the implied $\Psi(q(p))$ (blue line).

Scenario	Description	P	M	All
i)	Segmented markets $\xi^P = 0$, $\xi^M = 1$	3.86	15.44	6.64
ii)	Increase in M-Share $\xi + 0.10$	-0.67	15.94	3.83
iii)	Equalizing Dist. to M $\Gamma_P = \Gamma_M$	7.10	13.66	1.19
iv)	Equalizing Dist. to P $\Gamma_M = \Gamma_P$	2.65	-1.73	-2.77

Table A.14: Wage Effects for Robustness Specification

Note: The table shows percentage changes in average wages by firm type for P-firms, $E[\Delta w^P | z = P, \Omega^c, \Omega]$, and for M-firms, $E[\Delta w^M | z = M, \Omega^c, \Omega]$.

Scenario	Description	P	M	All
i)	Segmented markets $\xi^P = 0$, $\xi^M = 1$	4.62	-18.96	-18.79
ii)	Increase in M-Share $\xi + 0.10$	-1.19	2.28	2.25
iii)	Equalizing Dist. to M $\Gamma_P = \Gamma_M$	1.85	1.28	1.28
iv)	Equalizing Dist. to P $\Gamma_M = \Gamma_P$	3.73	-6.17	-6.10

Table A.15: Wage Effects for Robustness Specification - Unweighted

Note: The table shows percentage changes in average wages by firm type for P-firms, $E[\Delta w^P | z = P, \Omega^c, \Omega]$, and for M-firms, $E[\Delta w^M | z = M, \Omega^c, \Omega]$. In this specification, we weight all productivity equally for illustration purposes. Column 'All' aggregates according to sample weights in the baseline.

Scenario	Description	P	M	All
i)	Segmented markets $\xi^P = 0$, $\xi^M = 1$	2.68	-12.60	-11.89
ii)	Increase in M-Share $\xi + 0.10$	-1.11	4.98	4.70
iii)	Equalizing Dist. to M $\Gamma_P = \Gamma_M$	5.97	-19.15	-17.98
iv)	Equalizing Dist. to P $\Gamma_M = \Gamma_P$	2.07	-6.94	-6.52

Table A.16: Wage Effects for Baseline Specification - Unweighted

Note: The table shows percentage changes in average wages by firm type for P-firms, $E[\Delta w^P | z = P, \Omega^c, \Omega]$, and for M-firms, $E[\Delta w^M | z = M, \Omega^c, \Omega]$. In this specification, we weight all productivity equally for illustration purposes. Column 'All' aggregates according to sample weights in the baseline.