The Option Value of Occupations

Attila Gyetvai*

October 2024

The value of a job lies not only in the wage and amenities it pays, but also in the future job opportunities it enables. This paper quantifies the value of such opportunities—the option value—associated with occupations. I develop a model of job mobility within and across occupations and estimate it using linked Hungarian administrative data. I find that high-skill occupations offer higher wages and more stable employment; in turn, low-skill occupations feature higher amenities but larger switching costs to high-skill jobs. As a result, workers who start their careers in a high-skill occupation in the bottom 10 percent of wages surpass those who start in a low-skill occupation in the top 5 percent of wages within 5 years.

*Bank of Portugal & IZA, attila.gyetvai@bportugal.pt, attilagyetvai.com.

This paper is a revised version of the first essay of my Ph.D. dissertation at Duke University. I thank my advisors Peter Arcidiacono, Arnaud Maurel, Seth Sanders, and Pat Bayer for their guidance and support. The paper benefited from useful discussions with Carlos Carrillo-Tudela, Mónica Costa-Dias, Bruce Fallick, Fatih Guvenen, Gizem Koşar, Attila Lindner, Sergio Ocampo, Luigi Pistaferri, Fabien Postel-Vinay, Yongs Shin, Chris Taber, László Tétényi, and Hanna Wang, as well as comments by seminar participants at the Banks of Canada, Hungary, and Portugal, Bonn & IZA, Copenhagen, the Federal Reserve Banks of Chicago, Cleveland, and St. Louis, IFS, Oslo, McGill, McMaster, Minho, Queen's, Vienna, Western, and audiences at numerous conferences. I also thank Martín Teixeira for helpful research assistance. Further thanks to the Databank of the Center for Economic and Regional Studies for data access. Any and all errors are mine; in particular, the views expressed here are my own and do not necessarily reflect those of the Bank of Portugal or the Eurosystem. The paper previously circulated as "Job Mobility Within and Across Occupations." First draft: November 2019.

What determines the value of a job? One might argue that it is determined by the wage it pays and the non-wage amenities it provides. These measures, captured by the flow value of the job, are inherently static. However, dynamic measures matter more from a life cycle perspective—measures like wage growth within the job or future career paths that the job unlocks. These future opportunities, i.e., career paths that the worker may choose from, are captured by the option value of jobs. A job with a low flow value but a high option value can be more valuable than another one that pays well today but leads to subpar future opportunities.

In this paper I argue that the occupation of a particular job carries sufficient information to parse its flow vs. option value. Workers in various occupations receive promotions, outside job offers, and separation shocks at varying rates; they receive a varying share of their compensation in non-wage job amenities; furthermore, they face differing non-pecuniary costs to switch jobs. These mechanisms imply that the value of a job in a certain occupation is not only in its flow wage and non-wage compensation, but also in its potential career trajectories that vary across occupations. This dynamic view has far-reaching implications for understanding wage inequality across the life cycle.

I formalize this argument by proposing and estimating a model of job mobility within and across occupations. All model primitives are specific to a worker's current occupation and the occupation of offered jobs. In the model, different occupations feature different wage offers, capturing differences in pure returns to occupations. Workers in various occupations are promoted or demoted at varying rates, capturing occupation-specific skill accumulation. They also receive job offers and separation shocks at various rates across occupations, capturing occupation-specific labor market frictions. Occupations offer different non-wage amenities, resulting in occupation-specific compensating differentials. Finally, workers in different occupations face different non-pecuniary costs to switch into a certain occupation. Together, these mechanisms imply that jobs in various occupations differ not only in their flow values but also in the option values they afford their workers.

I estimate the structural model using linked Hungarian administrative data on half of the country's population: notably, these data contain administrative information on workers' occupational transitions at a (near-)daily frequency. The occupational classification maps to skill levels, creating a fine proxy for coarse skills in a data-driven way. Using these rich data, I uncover substantial occupational heterogeneity in the modeled mechanisms. I find that high-skill occupations offer higher wages and lower job separation rates than low-skill ones, and workers in high-skill occupations receive these better-paying offers more frequently than those in low-skill occupations. At the same time, low-skill occupations offer higher non-wage amenities. However, not everyone can take advantage of the wage gains from entering high-skill occupations: low-skilled workers face larger non-pecuniary costs to switch to these jobs, essentially locking them in lower wage trajectories. Taken together, these effects imply that high-skill jobs are more valuable than low-skill jobs: their lower levels of flow utility are offset by higher option values.

Using the structural estimates, I assess the contribution of occupational heterogeneity in each model mechanism to wage inequality. Upon entering the labor market, high-skilled workers who start in low-wage jobs expect rapidly rising wages: this steep wage growth stems from better wage offers in high-skill occupations. At the same time, low-skilled workers in high-wage jobs expect a sharp drop in their wages, due to more frequent job separations. Together, these forces imply that initial occupations shape workers' expected wage paths to a larger extent than their initial wages. Measures of model fit indicate that occupational heterogeneity in each of the captured mechanisms accounts for most of the empirical dispersion of wages. Allowing all mechanisms to interact with occupations fully accounts for the rising inequality of wages over the life cycle.

By its nature, this paper fits in multiple literatures. Fundamentally, I establish a new link between occupational mobility and wage inequality by accounting for heterogeneity within well-studied mechanisms. Thus, this paper relates to a line of work investigating the role of occupations in explaining the trends of wage inequality (Juhn, Murphy, and Pierce, 1993;

Kambourov and Manovskii, 2009a,b; Groes, Kircher, and Manovskii, 2015). Unlike these papers, I focus on life cycle inequality, i.e., the dispersion of wages among workers at certain points in their careers. More recently, Bayer and Kuhn (2023) provide reduced-form evidence linking life cycle wage inequality to occupations, distinguishing between job levels within occupations; however, they do not model wage dynamics arising from labor market frictions, non-wage amenities, or non-pecuniary job switching costs. Another related literature posits that occupational transitions result from workers' choices (Miller, 1984; Siow, 1984; McCall, 1990; Antonovics and Golan, 2012). Contrasting these papers, I argue that market frictions play an equally important role in understanding occupational mobility. More broadly, I contribute to papers that model career decisions in a dynamic discrete choice setting (Keane and Wolpin, 1997; Neal, 1999; Sullivan, 2010; Sullivan and To, 2014). In comparison, the present model emphasizes the role of occupation-specific labor market frictions.

This paper incorporates occupational heterogeneity to returns to skills, labor market frictions, and non-wage amenities. Each of these mechanisms have spurred vastly influential literatures. For returns to skills, see Card (1999) for a comprehensive survey, or more recently Ashworth, Hotz, Maurel, and Ransom (2021). For labor market frictions in heterogeneous job search models, see Postel-Vinay and Robin (2002); Cahuc, Postel-Vinay, and Robin (2006); Jolivet, Postel-Vinay, and Robin (2006); Taber and Vejlin (2020). For non-wage amenities and compensating differentials, see Rosen (1986); Sorkin (2018); Arcidiacono, Hotz, Maurel, and Romano (2020). I contribute to these literatures by incorporating occupational heterogeneity to each mechanism that seeks to explain wage inequality.

Substantively, this paper relates to two further, tangential literatures. An influential stream of papers attribute the dispersion of wages to worker- and firm-specific heterogeneity (Abowd, Kramarz, and Margolis, 1999; Card, Heining, and Kline, 2013; Card, Cardoso, Heining, and Kline, 2018; Bonhomme, Lamadon, and Manresa, 2019). I take a more structural approach and argue that occupation-specific heterogeneity accounts for the life cycle profile of wage inequality. Another tangentially related literature models the labor market

through the lens of multiple job ladders or island economies (Pilossoph, 2014; Wiczer, 2015; Busch, 2020; Jarosch, 2023; Carrillo-Tudela and Visschers, 2023). Focusing on a different set of questions, these papers analyze the dissipation of income or productivity shocks through the reallocation of resources across islands; however, they typically impose the same amount of frictions on searching across islands. I add to this literature by modeling heterogeneous frictions across occupations and demonstrating that occupations provide a key source of heterogeneity in understanding life cycle wage dispersion.

Methodologically, this paper brings the conditional choice probability approach, prevalent in the dynamic discrete choice literature (Hotz and Miller, 1993; Aguirregabiria and Mira, 2010; Arcidiacono and Ellickson, 2011), to job search. The core idea is that whenever individuals receive a job offer, they draw a cost or amenity shock—assuming that these shocks are drawn from a logistic distribution allows to express the model in terms of the job acceptance probabilities. This framework is presented in Arcidiacono, Gyetvai, Maurel, and Jardim (2022), which focuses on nonstationarity in job search (see also Llull and Miller, 2018, for an application to migration within Spain). Adding to this line of work, I add rich occupational heterogeneity to the model mechanisms and show identification in this extended setting.

Roadmap: The rest of the paper is structured as follows. Section 1 presents the data and descriptive evidence that high-skill occupations offer faster wage growth than low-skill ones. Section 2 introduces the model. Section 3 discusses the identification of the structural parameters. Section 4 contains and interprets the estimation results. Section 5 connects these results to life cycle wage inequality. Finally, Section 6 concludes the paper.

1 Descriptive Evidence

1.1 Data

I use matched employer-employee data from Hungarian administrative records covering half of the population, i.e., 4.6 million individuals, linked across 900,000 firms. These data have several strengths over other frequently used data sets: most importantly, they include detailed occupations from administrative sources, and they follow workers in continuous time.[1]

On the individuals' side, a de facto 50 percent random sample[2] of the Hungarian population are observed in the years 2003–11; every Hungarian citizen born on Jan 1, 1927 and every second day thereafter are included, yielding a sample of 4.6 million people. Labor market measures are recorded in up to two work arrangements at a time; importantly, one of these measures is occupation.[3] The occupational classification maps major occupational groups to skill content, proxied by the educational requirement of occupations within the group: Appendix Table A.1 presents this mapping for the occupations I include.

For the purposes of this paper, I restrict these rich data along several dimensions. First, I discard observations from 2011, the last year of the sample. The Hungarian occupation classification system was restructured in 2010, and the new classification is used from 2011. Unfortunately, the old and new occupation codes are not harmonized, and doing so would discard a substantial share of occupations. Second, I include males of age 22–50 who held at least one job in the sample, in an attempt to include as homogeneous analysis units in the sample as possible. By age 22, college students have presumably finished their education; the data do not contain information on educational attainment for most individuals, thus I resort to excluding younger workers. Furthermore, various pension rules are in effect for males from

[1]The data are constructed from continuous-time spells, and allow me to observe the approximate date of employer and occupation changes.

[2]I adopt the terminology of DellaVigna, Lindner, Reizer, and Schmieder (2017).

[3]4-digit occupations, based on the Hungarian Standard Classification of Occupations (HSCO). HSCO is similar in spirit to the Standard Occupational Classification (SOC) system by the BLS.

age 53; I drop older workers to ensure my results are not contaminated by their anticipatory behavior. Third, I include workers at privately owned firms. Hungary is a post-socialist welfare state, and thus has a large public sector: 30 percent of worker-month observations in the data are working in some form of a public sector job. Since these jobs are contracted differently than private sector jobs, including them would compromise the homogeneity of the sample. Fourth, I drop individuals who work in agricultural occupations and armed forces as transitions into and out of these occupations occur infrequently. Furthermore, I add office clerks to commercial occupations as they are comparable in skill content, and because they make up a small part of the sample on their own. The seven remaining occupations are Managers, Professionals, Technicians, Commercial occupations, Industry occupations, Machine operators, and Elementary occupations: see Appendix Table A.1. Fifth, finally, I only consider data on the primary work arrangement for all workers, even if they reportedly work in multiple parallel jobs.

These rich data accommodate the enormous requirements of estimating the model. I consider a discrete distribution of jobs, comprised of a handful of occupations and wage bins. Besides the seven occupations, I discretize wages into ten bins: I define the first wage bin as between 75 and 100 percent of the effective minimum wage, and bins 2 to 10 as nine-quantiles of the conditional wage distribution, truncated at the minimum wage. Therefore, job-to-job transitions fall into one of 4,900 cells:[4] Appendix Figure A.1 presents the entire job-to-job transition matrix. Most transitions occur within the same job. Conditional on an occupational switch, workers tend to move into occupations that are similar in terms of skill content to their current one. However, a sizable fraction of transitions occur from low-skill to high-skill occupations and vice versa.

1.2 Young workers' wage growth across occupations

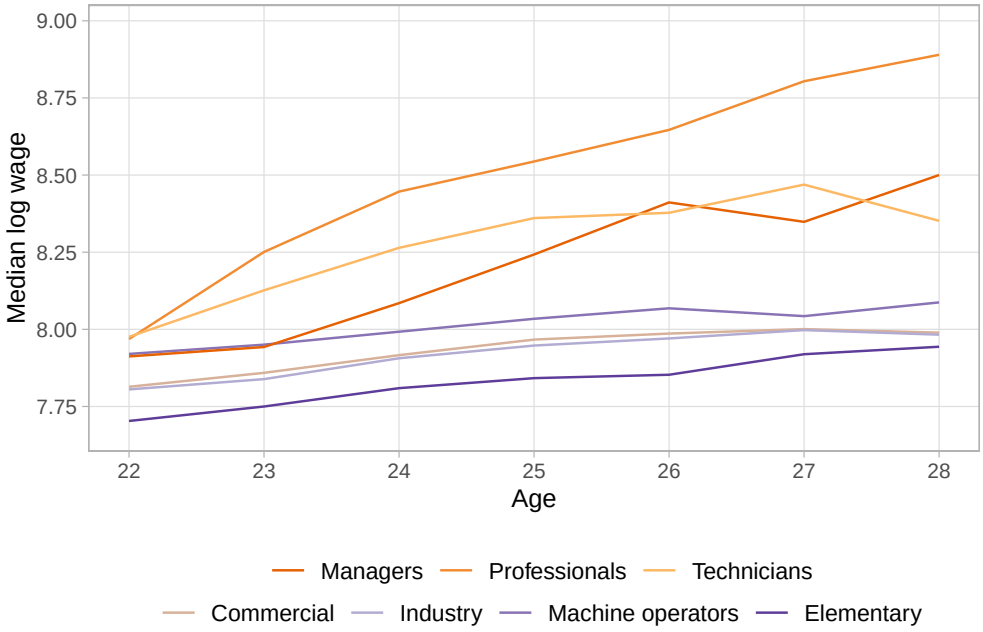
I now show that initial wages mask substantial occupational differences in subsequent wage growth. Figure 1.1 illustrates that occupations offer diverging wage trajectories to their workers. Young workers earn similar wages upon entering the labor market: for example, the median wages of office clerks and machine operators coincide at age 22. However, those who start their careers in high-skill occupations experience much faster wage growth than those in low-skill occupations. Ten years into their careers, office clerks earn 80 percent higher wages than machine operators.

Occupations offer diverging wage paths for workers at all wage levels. Figure 1.2 contrasts the observed wage paths of workers who start their careers in a low-wage job in a high-skill occupation to those of workers who start in high-wage low-skill jobs. At age 22, workers whose first job is in a low-skill occupation but pays above the median earn 58 percent higher wages than workers who start in a high-skill occupation but earning below median. However, these initial differences disappear in 3 years: high-skilled workers make up for their lower wages and quickly surpass their low-skill peers, who experience hardly no wage growth. By age 28, initially low-paid high-skilled workers earn 13 percent more on average than their low-skill peers—especially professionals whose wage premium reaches 33 percent.

Higher-skill occupations offering upward wage mobility begets the question: how can workers in low-skill occupations enter these more lucrative jobs? Upon switching into a higher-skill occupation, will they immediately earn more? Or, alternatively, would it be worthwhile for them to accept a low-paying offer in a high-skill occupation if it opens up better opportunities in the future? I attend to these questions in the remainder of this paper.

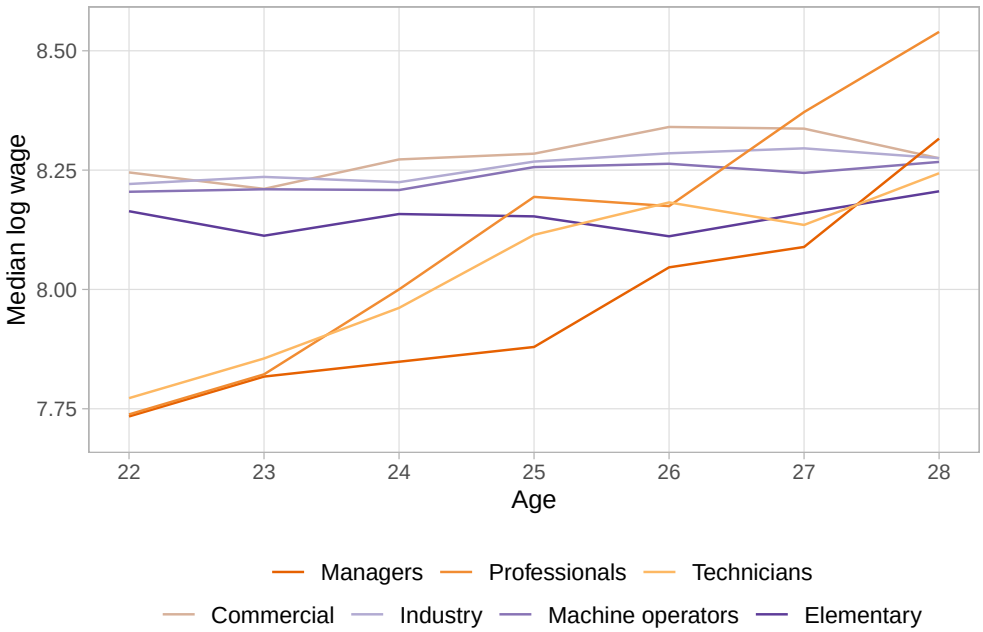
[4] $7 \cdot 10 \times 7 \cdot 10 = 4,900$ job-to-job transition cells.

Figure 1.1: Diverging occupational wage paths early in the life cycle



Notes: Median log wages of workers entering the labor market by age 22. Lines denote aggregate wages for workers whose first job is in respective occupation.

Figure 1.2: Initially low-paid high-skilled workers catch up



Notes: Median log wages of workers entering the labor market by age 22. Lines denote aggregate wages for workers whose first job is in respective occupation: high-skilled workers (managers, professionals, technicians) with low initial wages (below median wage at age 22), low-skilled workers (commercial, industry, machine operators, elementary) with high initial wages (above median wage at age 22).

2 Model

This paper proposes a job posting model with numerous occupational employment states as well as a non-employment state. Contrary to wage posting models, firms post non-negotiable *job offers* where a job is an occupation-wage pair. From the individuals' perspective, job offers arrive at rates that are specific to their current occupation and the occupation of the job offer. Upon receiving an offer, they decide whether to accept it: their decision is governed by the cost of switching to the new job. This switching cost is stochastic, capturing the fact that individuals do not know ex ante whether they would accept a particular offer. I assume that the switching costs are logistically distributed. As a consequence, I am able to express the model in terms of the conditional choice probabilities (CCPs) — this object captures the probability that a worker will accept a particular job offer, conditional on their current job.

2.1 Notation

I ease notation by adhering to a set of guiding principles. In general, lower indices refer to origin states and upper indices refer to destination states. For occupations, I reserve the $(a, b, \ldots)$ indices and denote the typical occupation by o. For wages, I reserve the $(i, j, \ldots)$ indices and denote the typical wage rate by w. I denote jobs as an occupation–wage pair (a, i). Non-employment is denoted by n.

Putting these pieces together, the object p_{ai}^{bj}, as an example, denotes the probability of accepting a job offer in occupation b with wage j when the current job is in occupation a and pays i. Furthermore, I omit unobserved heterogeneity from the discussion of the model and its identification for the sake of clarity; I introduce types in Section 4.

2.2 Value functions

Time is continuous. At any point in time, an individual is either employed in a job (a, i) or not currently employed n. For an individual who is currently employed in job (a, i), three

events may occur at any given instance. First, they may be promoted or demoted to another wage level w within their current occupation a: wage changes occur at the rate χ_{ai}^{aw}, specific to the occupation as well as the origin and destination wages, and lead to an immediate and costless transition. Second, they may separate from their current job at the separation rate δ_a: job separations are exogenous and lead to immediate non-employment in the model. Third, they may receive an offer from occupation o: these offers arrive at the rate λ_a^o which is specific to the pair of origin and destination occupations. The ex ante probability of receiving offers is integrated over all occupations that the offer may come from. If none of these events occur, time gets discounted at the rate ρ.

The attained value is comprised of the flow utility and the option value of the current job. The flow utility u_{ai} varies with the current occupation and wages.[5] The option value is the ex ante expected continuation value from the current job, i.e., the expected maximum value among attainable options, integrated over the set of possible future states: promotion/demotion, job separation, and job transitions. In contrast to an exogenous wage or separation shock, upon which the worker is forced to a new wage or out of employment, accepting an offer is a choice. When workers receive an offer, they draw a switching cost $\tilde{c}_a^o$ from a known distribution with mean c_a^o and compare the value of the offered job, net of the cost of switching, to the value of staying in the current job.[6] Putting all the pieces together, the value of employment in job (a, i) is written as

$$\left(\sum_o \lambda_a^o + \sum_w \chi_{ai}^{aw} + \delta_a + \rho\right) V_{ai} = u_{ai} + \sum_w \chi_{ai}^{aw} V_{aw} + \delta_a V_n + \mathbb{E}_{o,w,\tilde{c}}[\lambda_a^o \max\{V_{ow} - \tilde{c}_a^o, V_{ai}\}]. \tag{2.1}$$

The value of non-employment is analogous to the above. An individual not in employment incurs the flow utility u_n and may receive a job offer from any occupation at rates specific to non-employment. If an offer arrives, they draw a switching cost which determines whether

[5] I discuss the structure I impose on flow utilities in Section 3.

[6] These stochastic switching costs can be equivalently expressed as deterministic costs amended by preference shocks drawn with job offers; see Appendix B.

they would accept the offer. Formally, the value function is

$$\left(\sum_o \lambda_n^o + \rho\right) V_n = u_n + \mathbb{E}_{o,w,\tilde{c}}[\lambda_n^o \max\{V_{ow} - \tilde{c}_n^o, V_n\}]. \tag{2.2}$$

2.3 CCP structure

I assume that switching costs are drawn from the logistic distribution with mean c_a^b. Combined with the assumption that wages are discrete with p.m.f. f^{ow}, I can express the value functions in terms of conditional choice probabilities, i.e., the probability of accepting an offer conditional on receiving it:[7]

$$\rho V_{ai} = u_{ai} + \sum_w \chi_{ai}^{aw}(V_{aw} - V_{ai}) + \delta_a(V_n - V_{ai}) - \sum_{o,w} \lambda_a^o \log(1 - p_{ai}^{ow}) f^{ow} \tag{2.3}$$

and

$$\rho V_n = u_n - \sum_{o,w} \lambda_n^o \log(1 - p_n^{ow}) f^{ow}. \tag{2.4}$$

The logistic assumption on the switching costs implies a particular structure on choice probabilities, a structure on which my identification strategy relies. Using this distributional assumption, the probability of accepting a job offer (b, j) conditional on receiving it when the current job is (a, i) can be written in terms of the value functions and mean switching costs as

$$p_{ai}^{bj} = \frac{\exp\left(V_{bj} - V_{ai} - c_a^b\right)}{1 + \exp\left(V_{bj} - V_{ai} - c_a^b\right)}. \tag{2.5}$$

Consequently, the probability of accepting (a, i) conditional on arrival when in (a, i) is

$$p_{ai}^{ai} = \frac{\exp\left(V_{ai} - V_{ai} - c_a^a\right)}{1 + \exp\left(V_{ai} - V_{ai} - c_a^a\right)} = \frac{\exp\left(-c_a^a\right)}{1 + \exp\left(-c_a^a\right)}. \tag{2.6}$$

[7] See Appendix B for details.

It follows that the probability of accepting jobs from the same occupation that offers the same wage is constant across wage levels:

$$p_{ai}^{ai} = p_{aj}^{aj} \tag{2.7}$$

for all i and j. Section 3 discusses how I utilize this structure for identification.

3 Identification

The core idea behind identification is to match job-to-job and non-employment-to-job hazard rates to the structural parameters of the model. Here I unfold the main identification argument in a sequential fashion. The identification strategy presented here builds on Arcidiacono, Gyetvai, Maurel, and Jardim (2022) which models the search behavior of employed and unemployed individuals in a nonstationary environment. I build on this approach by bringing in various forms of occupational heterogeneity. This section demonstrates how incorporating this occupational heterogeneity extends this framework. In contrast with this companion paper, however, I do not consider nonstationarity on the non-employment-to-job side for exposition's sake: combining the two approaches would be an interesting extension.

3.1 Hazards

The identification of hazards is separate from the structural parameters of the model. I model four set of hazards: those of job-to-job, job-to-non-employment, non-employment-to-job, and within-job wage transitions. I use a competing risk model with multiple spells. Since the model does not accommodate heterogeneity in tenure on the current job, hazard rates are assumed to be constant over time; that is, I assume durations follow an exponential distribution. Identification of the hazards in this setting is well understood and, thus, is not discussed here.[8] Note that some hazard rates directly identify certain structural parameters:

[8]See, e.g., Cox (1959, 1962); Tsiatis (1975).

the hazard of within-job wage changes identifies χ_{ai}^{aj} and the hazard of job-to-non-employment transitions identifies δ_a.

3.2 Structural parameters

The backbone of my identification argument is that, by definition, the hazard rate of transitioning from job (a, i) to (b, j) is

$$h_{ai}^{bj} = \lambda_a^b f^{bj} p_{ai}^{bj} \tag{3.1}$$

where λ_a^b is the arrival rate of offers from b to a, $f^{b\cdot}$ is the distribution of offered wages in b, and p_{ai}^{bj} is the probability of accepting an offer (b, j) when the current job is (a, i), conditional on receiving that offer.

The key identification argument is that fast offers yield more transitions at high wages while strong preferences spur churn at all wage levels. If workers know that offers from a certain occupation arrive frequently, they can rest assured that if they reject a low-wage offer now, a high-wage one will arrive soon. Conversely, if workers have strong preferences to work in a certain occupation, they would accept an offer from it at any wage level and they would not leave once they enter. Therefore, variation in the hazard rates across occupations at various wage levels separate offers from choices. I now expand on this high-level argument.

Offered wage distribution: Consider the hazard of moving from (a, i) to (a, i):

$$h_{ai}^{ai} = \lambda_a^a f^{ai} p_{ai}^{ai}. \tag{3.2}$$

As noted before in Equation 2.7, the offer-contingent probability to switch from a given job to the same job does not vary with the level of wages. Therefore, taking the ratio of the hazards of switching into the same job, the arrival rate and the switching probabilities

cancel:

$$\frac{h_{ai}^{ai}}{h_{aj}^{aj}} = \frac{f^{ai}}{f^{aj}}. \tag{3.3}$$

Since the distribution of offered wages sums to 1, it follows that[9]

$$f^{ai} = \frac{h_{ai}^{ai}}{\sum_w h_{aw}^{aw}}. \tag{3.4}$$

Note that the structure of choice probabilities allows for the identification of offered wages within, but not across, occupations. For example, wages in managerial job offers are drawn from the same distribution, regardless of whether the offer goes to technicians or machine operators. This result emerges from the fact that $p_{ai}^{bi} \neq p_{aj}^{bj}$ for $a \neq b$.

Offer arrival rates (J2J): Consider the log odds of accepting a job (b, j) while being employed in (a, i), denoted by ϖ_{ai}^{bj}:

$$\varpi_{ai}^{bj} \equiv \log\left(\frac{p_{ai}^{bj}}{1 - p_{ai}^{bj}}\right) = \log\left(\frac{h_{ai}^{bj}}{\lambda_a^b f^{bj} - h_{ai}^{bj}}\right) \tag{3.5}$$

using the fact that $p_{ai}^{bj} = h_{ai}^{bj} / \left(\lambda_a^b f^{bj}\right)$.[10] The only unknown parameter determining the odds is the offer arrival rate, as the hazard of switching jobs and the offered wage distribution have already been identified.

I start by identifying the arrival rates of offers from the same occupation as the current one, λ_a^a. Using the value of employment in Equation 2.3, the log odds of accepting an offer from the current occupation is

$$\varpi_{ai}^{aj} = V_{aj} - V_{ai} - c_a^a. \tag{3.6}$$

[9]Summing Equation 3.3 over wages yields $\frac{\sum_w h_{aw}^{aw}}{h_{ai}^{ai}} = \frac{\sum_w f^{aw}}{f^{ai}} = \frac{1}{f^{ai}}$.

[10]From Equation 3.1: $\frac{p_{ai}^{bj}}{1-p_{ai}^{bj}} = \frac{h_{ai}^{bj}/\left(\lambda_a^b f^{bj}\right)}{1-h_{ai}^{bj}/(\lambda_a^b f^{bj})} = \frac{h_{ai}^{bj}}{\lambda_a^b f^{bj} - h_{ai}^{bj}}$.

Consider a pair of log odds, one associated with moving across jobs that pay different wages within the same occupation and another associated with the reverse move. Taking two such pairs, it holds that[11]

$$\varpi_{ai}^{aj} + \varpi_{aj}^{ai} = \varpi_{ak}^{a\ell} + \varpi_{a\ell}^{ak} = -2c_a^a. \tag{3.7}$$

The offer arrival rates from the current occupation are readily identified from Equation 3.7:

$$\lambda_a^a = \frac{\left[h_{ai}^{aj} f^{ai} + h_{aj}^{ai} f^{aj}\right] h_{ak}^{a\ell} h_{a\ell}^{ak} - \left[h_{ak}^{a\ell} f^{ak} + h_{a\ell}^{ak} f^{a\ell}\right] h_{ai}^{aj} h_{aj}^{ai}}{f^{ai} f^{aj} h_{ak}^{a\ell} h_{a\ell}^{ak} - f^{ak} f^{a\ell} h_{ai}^{aj} h_{aj}^{ai}}. \tag{3.8}$$

Now I turn to identifying the arrival rates of offers from different occupations than the current one, λ_a^b. Again, using the value of employment in Equation 2.3 the log odds of accepting an offer from the current occupation can be expressed as

$$\varpi_{ai}^{bj} = V_{bj} - V_{ai} - c_a^b. \tag{3.9}$$

Taking two such job pairs, it holds that

$$\varpi_{ai}^{bj} + \varpi_{bj}^{ai} = \varpi_{ak}^{b\ell} + \varpi_{b\ell}^{ak} = -\left(c_a^b + c_b^a\right). \tag{3.10}$$

Note that these log odds contain the offer arrival rates from a to b λ_a^b as well as the reverse λ_b^a. Therefore, replicating Equation 3.10 for another two job pairs (a', i')–(b', j') and (a', k')–(b', ℓ') identifies both arrival rates. Appendix C provides more details.

Choice probabilities (J2J): With the offer arrival rates at hand, the choice probabilities are readily identified from the definition of hazards:

$$h_{ai}^{bj} = \lambda_a^b f^{bj} p_{ai}^{bj}. \tag{3.11}$$

[11] Note that $\varpi_{ai}^{ai} = \varpi_{aj}^{aj}$ also holds. However, I already extracted all the information contained in offers from the same wage bins in the identification of the wage offer distribution f^{bj}.

Switching costs (J2J): The switching costs come from the identifying equations for the offer arrival rates. Equation 3.7 readily identifies the cost of switching to a job in the same occupation:

$$c_a^a = -\frac{\varpi_{ai}^{aj} + \varpi_{aj}^{ai}}{2}. \tag{3.12}$$

However, the equivalent equations for cross-occupation switches cannot separately identify the cost of switching from occupation a to b and the reverse, b to a. Rather, identification comes from the aggregation of occupations by skill content, observed in the data. The skill content of occupations is declining by the design of the occupation classification system, presented in Table A.1

I impose a restriction of relative symmetry: for occupations $a \neq b$,

$$c_a^b = \alpha_{s_a}^{s_b}\, c_b^a \tag{3.13}$$

where s_a is the skill content of occupation a. The α multipliers are the same for commercial, industry, and machine operators. I estimate 11 separate multipliers; Figure 3.1 displays them.

Under these restrictions, Equation 3.10 can be rewritten as

$$\varpi_{ai}^{bj} + \varpi_{bj}^{ai} = -\left(1 + \alpha_{s_a}^{s_b}\right) c_a^b. \tag{3.14}$$

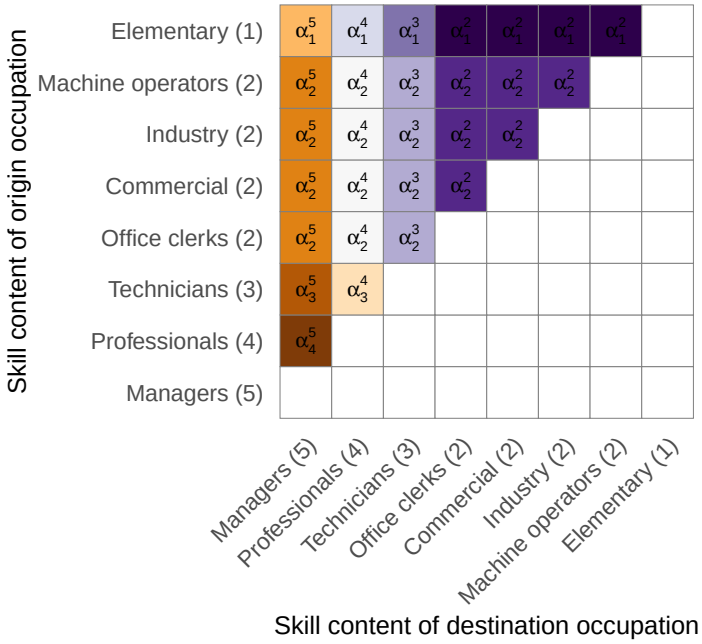
The same logic extends to cycles of three job switches as well:

$$\varpi_{ai}^{bj} + \varpi_{bj}^{ck} + \varpi_{ck}^{ai} = -\left(c_a^b + c_b^c + \alpha_{s_a}^{s_c}\, c_a^c\right) \qquad \text{and} \tag{3.15}$$

$$\varpi_{bi}^{aj} + \varpi_{aj}^{ck} + \varpi_{ck}^{bi} = -\left(\alpha_{s_a}^{s_b}\, c_a^b + c_a^c + \alpha_{s_b}^{s_c}\, c_b^c\right). \tag{3.16}$$

This system of equations jointly identifies the unidirectional costs as well as the α multipliers,

Figure 3.1: Switching cost multipliers



and, thus, the entire matrix of switching costs.

Offer arrival rates (N2E): Now I turn to structural parameters for those not in employment. Consider the log odds of accepting an offer (b, j) from non-employment:

$$\varpi_n^{bj} = V_{bj} - V_n - c_n^b. \tag{3.17}$$

Combining this log odds with the log odds of accepting an offer from the same occupation and another wage, (b, i), it holds that

$$\varpi_n^{bj} - \varpi_n^{bi} = V_{bj} - V_{bi} = \varpi_{bi}^{bj} + c_b^b. \tag{3.18}$$

Since all other parameters have been identified by now, this equation identifies λ_n^b.

Choice probabilities (N2E): Given the N2E offer arrival rates, the choice probabilities

fall out from the hazard definition:

$$h_n^{bj} = \lambda_n^b f^{bj} p_n^{bj}. \tag{3.19}$$

Flow utilities (J2J, N2E) and switching costs (N2E): I identify the remaining structural parameters together in a system of linear equations. The log odds of accepting a job offer are

$$\begin{aligned}\varpi_{ai}^{bj} = &\frac{1}{\delta_b + \rho}\left(u_{bj} + \sum_w \chi_{bj}^{bw}(\varpi_{bj}^{bw} + c_b^b) - \sum_{o,w}\lambda_b^o \log(1 - p_{bj}^{ow}) f^{ow}\right) \\ &- \frac{1}{\delta_a + \rho}\left(u_{ai} + \sum_w \chi_{ai}^{aw}(\varpi_{ai}^{aw} + c_a^a) - \sum_{o,w}\lambda_a^o \log(1 - p_{ai}^{ow}) f^{ow}\right) \\ &+ \frac{\delta_b - \delta_a}{(\delta_b + \rho)(\delta_a + \rho)}\left(u_n - \sum_{o,w}\lambda_n^o \log(1 - p_n^{ow}) f^{ow}\right) - c_a^b\end{aligned} \tag{3.20}$$

and

$$\begin{aligned}\varpi_n^{bj} = &\frac{1}{\delta_b + \rho}\left(u_{bj} + \sum_w \chi_{bj}^{bw}(\varpi_{bj}^{bw} + c_b^b) - \sum_{o,w}\lambda_b^o \log(1 - p_{bj}^{ow}) f^{ow}\right. \\ &\left. - u_n - \sum_{o,w}\lambda_n^o \log(1 - p_n^{ow}) f^{ow}\right) - c_n^b.\end{aligned} \tag{3.21}$$

Equations 3.23 and 3.24 are linear in the unknown parameters u_{ai}, u_{bj}, u_n, and c_n^b.[12] Therefore writing these equations for all possible $(a,i)-(b,j)$ combinations yields a linear system of equations. However, the system cannot identify all parameters separately; therefore, I impose additional structure on them.

I parametrize u_{ai} to be an occupation-specific level shift of a common log wage profile:

$$u_{ai} = \psi_a + \beta \log \mathrm{w}_i \tag{3.22}$$

where w_i denotes the wage level associated with wage bin i. This parametrization aids the

[12] As standard in the literature, I do not estimate the discount rate ρ but rather set it to 0.05.

interpretation of the results as I can quantify the occupational differences in wage profiles in utility and in monetary terms. Furthermore, I restrict c_n^b to vary with the skill content of the occupation of the offer. That is, I flexibly estimate five separate switching cost parameters out of non-employment to occupations in each skill level. Putting these parametrizations together, the identifying equations become

$$\kappa_{ai}^{bj} = \frac{1}{\delta_b + \rho}\,\psi_b - \frac{1}{\delta_a + \rho}\,\psi_a + \left(\frac{\log \mathrm{w}_j}{\delta_b + \rho} - \frac{\log \mathrm{w}_i}{\delta_a + \rho}\right)\beta + \frac{\delta_b - \delta_a}{(\delta_b + \rho)(\delta_a + \rho)}\,u_n \tag{3.23}$$

and

$$\kappa_{n}^{bj} = \frac{1}{\delta_b + \rho}\,\psi_b + \frac{\log \mathrm{w}_j}{\delta_b + \rho}\,\beta - \frac{1}{\delta_b + \rho}\,u_n - c_n^b \tag{3.24}$$

where κ_{ai}^{bj} and κ_{n}^{bj} collect all known terms; i.e.,

$$\begin{aligned}\kappa_{ai}^{bj} = \varpi_{ai}^{bj} &+ \frac{1}{\delta_b + \rho}\left(\sum_{o,w} \lambda_b^o \log(1 - p_{bj}^{ow}) f^{ow} - \sum_{w} \chi_{bj}^{bw}(\varpi_{bj}^{bw} + c_b^b)\right) \\ &- \frac{1}{\delta_a + \rho}\left(\sum_{o,w} \lambda_a^o \log(1 - p_{ai}^{ow}) f^{ow} - \sum_{w} \chi_{ai}^{aw}(\varpi_{ai}^{aw} + c_a^a)\right) \\ &+ \frac{\delta_b - \delta_a}{(\delta_b + \rho)(\delta_a + \rho)} \sum_{o,w} \lambda_n^o \log(1 - p_n^{ow}) f^{ow} + c_a^b\end{aligned}$$

and

$$\kappa_{n}^{bj} = \varpi_{n}^{bj} + \frac{1}{\delta_b + \rho}\left(\sum_{o,w} \lambda_b^o \log(1 - p_{bj}^{ow}) f^{ow} - \sum_{w} \chi_{bj}^{bw}(\varpi_{bj}^{bw} + c_b^b) - \sum_{o,w} \lambda_n^o \log(1 - p_n^{ow}) f^{ow}\right).$$

The linear system admits an exact solution, which concludes our tour of identification.

3.3 Discussion

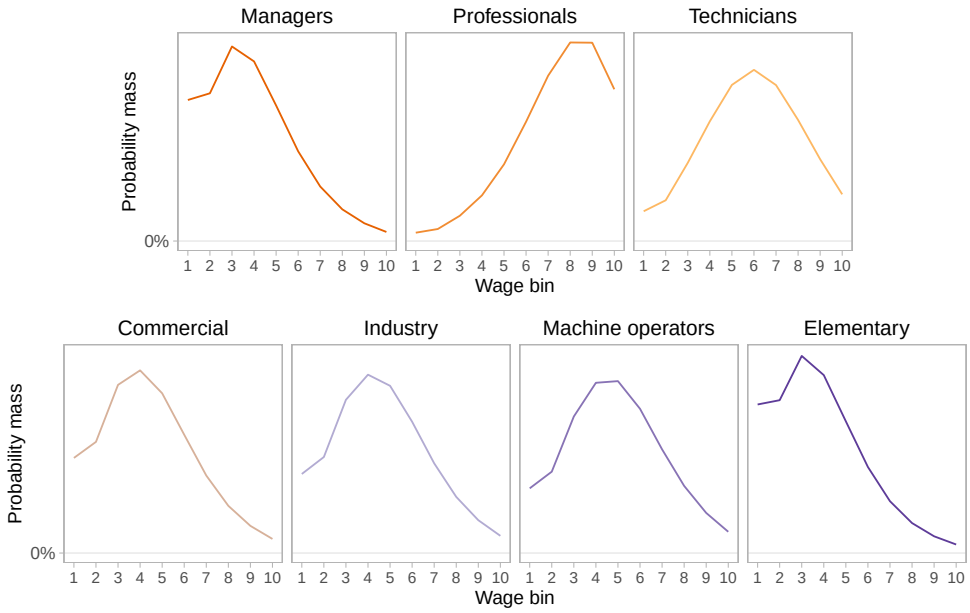
Like all economic models, the one presented here is a stylized depiction of reality and, as such, trades off simplicity for realism. At this point, it is worth taking a step back to discuss

these tradeoffs.

The crux of job search models is to separate "choices" from "offers"—that is, to separately identify determinants of the job search process that a worker can control from those that they cannot. In my model, offers are specific to origin and destination occupations and the wages at the destination job. Offers arrive at different rates to workers currently in different occupations; however, the offered wages are drawn from the same distribution for each destination occupation. While this feature is shared with most wage posting models (cf. Burdett and Mortensen, 1998), its implications are amplified in this setting. To the extent that workers in low-skill occupations receive high-wage offers from high-skill occupations, but they are not observed to make such transitions in the data, will seep into their preference and cost parameters.

I also remark that I omit certain sources of wage inequality that has been in the forefront of the job search literature. Prior work has discussed the distributional implications of modeling worker-, firm-, and match-specific heterogeneity in a general equilibrium setting (Postel-Vinay and Robin, 2002; Cahuc, Postel-Vinay, and Robin, 2006; Lise, Meghir, and Robin, 2016; Bagger and Lentz, 2019; Taber and Vejlin, 2020). Furthermore, human capital accumulation has been shown to account for wage dynamics (Burdett, Carrillo-Tudela, and Coles, 2011; Bagger, Fontaine, Postel-Vinay, and Robin, 2014; Taber and Vejlin, 2020). Here I take a partial equilibrium approach with ex ante heterogeneity due to occupations, and ex post heterogeneity due to the realizations of the stochastic switching costs. The effects of the omitted channels are subsumed into the wage offers. Although it is an open empirical question, my approach may yield similar results to the extent that similar occupation-specific offer distributions arise endogenously in general equilibrium. Considering these channels is subject to future research, which I return to in the concluding section of this paper.

Figure 4.1: Offered wages



Notes: Cumulative distribution functions and accepted wages in Appendix Figure E.2.

4 Results

[In progress: results with within-job wage promotions]

I now take the model to the data. I estimate the parameters of the structural model using maximum likelihood. I impose the model structure on the hazards of job-to-job and job-to-unemployment transitions: I express the hazards as a function of the structural parameters and maximize the likelihood of these constructed hazards fitting the empirical transition patterns. I model the hazards in a competing risk framework with two-sided censoring and exponential hazards. In an additional step, I introduce unobserved heterogeneity among workers and estimate this new model using an EM algorithm (Arcidiacono and Miller, 2011). This procedure is efficient yet computationally light: the likelihood function only takes in aggregated data in each origin and destination job pair, instead of the entirety of transitions. Appendix D discusses the estimation procedure in detail.

Table 4.1: Offer arrival and job separation rates

Current occupation	Offer arrival rates				Job sep. rates
	Total	Share			
		Own	High	Low	
Managers	2.74	17.3	25.1	74.9	0.21
Professionals	3.96	14.3	32.1	67.9	0.24
Technicians	3.04	17.1	24.5	75.5	0.25
Commercial	1.16	48.1	7.3	92.7	0.43
Industry	0.95	60.0	4.4	95.6	0.34
Machine operators	1.85	33.2	5.0	95.0	0.33
Elementary	1.20	47.9	9.7	90.3	0.99
Out of labor force	0.93	–	12.9	87.1	–

Notes: Offer arrival rates denote share of offers within a worker's current occupation, arriving from one's own/high-skill/low-skill occupations. Job separation rates are annual. All offer arrival rates in Appendix Figure E.3.

Table 4.2: Aggregate switching costs

Current occupation	Switching costs		
	Own	High-skill	Low-skill
Managers	0.06	0.08	0.53
Professionals	0.06	0.05	0.70
Technicians	0.05	0.03	0.24
Commercial	0.10	0.20	1.18
Industry	0.03	1.00	0.28
Machine operators	0.04	2.07	0.48
Elementary	0.86	5.68	1.07
Out of labor force	–	0.56	0.28

Notes: Mean switching costs from one's current occupation to own/high-skill/low-skill occupations. All switching costs in Appendix Figure E.4.

Table 4.3: Flow utilities and option values

Occupation	Flow utilities			Values		
	β	ψ_a	Comp. diff.	Full	Min	Max
Managers	1.42	-1.49	0.26	20.0	207.4	211.3
Professionals		-1.83	0.21	20.8	208.6	211.7
Technicians		-1.21	0.32	19.5	207.7	211.1
Commercial		0.72	1.26	16.2	204.8	208.0
Industry		0.84	1.36	16.2	205.9	209.9
Machine operators		0.40	1.00	16.8	206.7	210.5
Elementary		5.07	26.52	12.1	204.8	206.7
Out of labor force		–	–	124.6	–	

Notes: Compensating differentials: willingness-to-pay to switch to machine operating, relative to current wage. Full values: average of overall values normalized by flow utilities across wages in occupation. Min/max value: unnormalized values.

4.1 Baseline estimates

In the model, high-skill occupations offer faster wage growth than low-skill ones. As shown on Figure 4.1, high-skill occupations offer higher wages than low-skill ones. The contrast is especially stark for professionals vs. elementary occupations: while 28 percent of professional offers come from the highest wage bin, 54 percent of offers from elementary occupations come from the lowest wage. Therefore, differential wage offers across occupations would give rise to diverging wage paths, akin to the empirical patterns. However, these forces do not impact wage trajectories in isolation: even though low-skill offers pay little, they are still rarely rejected (as shown in Appendix Figure E.2). The other mechanisms in the model shed light on the sources of this behavior.

The offer arrival rates in Table 4.1 tell two different stories about high- and low-skill occupations. Workers in high-skill occupations receive 2.74–3.96 offers annually, while those in low-skill occupations receive about one less offer, ranging from 0.95–1.85 offers per year. Overall, offers come from low-skill occupations much more frequently than from high-skill ones. This pattern is shared by current high- and low-skilled workers as well as individuals out of the labor force. However, the differences are smaller for current high-skilled workers: they receive high-skill offers with a five time higher probability than current low-skilled workers (24.5–32.1 vs. 4.4–9.0 percent) and twice as frequently as those who are not working (24.5–32.1 vs. 12.9 percent). Low-skilled workers are more likely to receive an offer from the occupation they are currently working in (33.2–60.0 vs. 14.3–17.3 percent); however, conditional on offers from occupations in one's current skill level, offers are less likely to come from their own occupation. These patterns may emerge as a result of the transferability of skills across high- and low-skill occupations. On one hand, current high-skilled workers likely possess the necessary skills for high-skill occupations, thus they get high-skill offers more frequently—but they also get low-skill offers relatively frequently as they can be a good match there as well. On the other hand, current low-skilled workers rarely get the opportunity to switch to high-skill occupations.

The job separation rates in the last column of Table 4.1 worsen the outlooks of low-skilled workers. These jobs are less stable: workers in low-skill occupations separate to non-employment at much faster rates than those in high-skill ones. Elementary jobs are especially fragile: these workers lose their job once a year while only one in four managers separates to non-employment in a given year. These elementary occupations, such as janitors and helpers, substitute unemployment: they require no formal qualifications, pay little, and are typically short-term arrangements. Therefore, high-skill occupations are valuable not only due to their faster wage growth but also their higher retention rates.

Let's turn to what the data tell us about the behavior of workers once they get a job offer. Upon the offer's arrival, they learn the cost of switching from their current job to the new one, and decide whether they accept the offer. Table 4.2 displays aggregate measures of these cost realizations. Overall, the least costly switch is within one's current occupation, more costly to switch to another occupation at a similar skill level, and most costly to switch to occupations at another skill level. Moving to another skill level is associated with a five times higher cost than staying at one's current skill level. Once again, high- and low-skill occupations paint two different pictures: "downskilling" for high-skilled workers is less costly than "upskilling" for low-skilled workers. High-skilled workers have to pay a cost in the range of 0.03–0.08 to switch to another high-skill job and costs of 0.24–0.70 to switch to low-skill jobs. Low-skilled workers face much higher costs in both directions: 0.28–1.18 for another low-skill job and 0.20–5.68 for transitions to a high-skill one. These large costs help explain why low-skilled workers reject high-skill offers at high rates. Separating to non-employment is of no help to ease these transitions either: moving into a high-skill occupation from non-employment demands a cost of 0.56, while it is a third of that, 0.28, for low-skill occupations.

Finally, I discuss the value of jobs in high- vs. low-skill occupations. This value is comprised of the flow utility that workers instantaneously incur, as well as the option value of being in a certain job. Looking at the flow utilities in Table 4.3, low-skill jobs yield higher utility than high-skill ones for the same wage. I translate these differences into compensating

differentials: the third column of the table shows how much a worker in a certain occupation would have to be compensated to become a machine operator. That is, the compensating differential for a worker in occupation a making wage $\bar{\mathrm{w}}_a$, denoted by $\mathrm{w}_a^{\mathrm{MO}}$, satisfies the equation

$$\psi_a + \beta \log \bar{\mathrm{w}}_a = \psi_{\mathrm{MO}} + \beta \log \mathrm{w}_a^{\mathrm{MO}}. \tag{4.1}$$

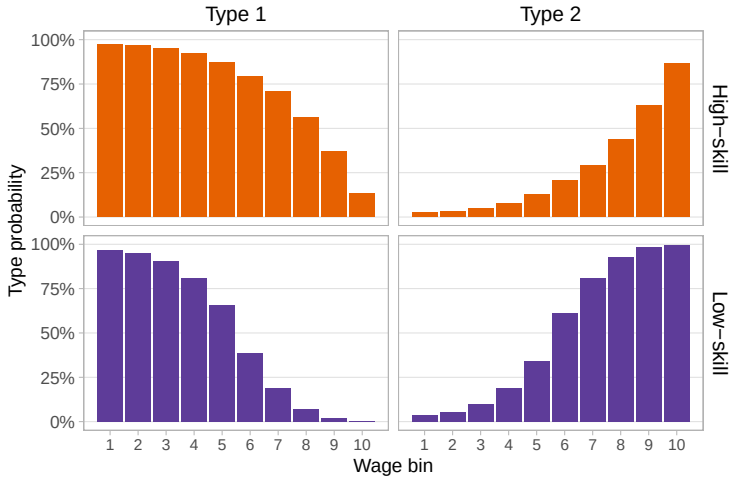
Current high-skilled workers would accept a machine operating job for a fraction of their current pay, while current low-skilled workers would need much higher wage offers. For instance, professionals would take that job for 21 percent of their current wage but industry workers would need 36 percent higher pay. The results are especially stark for elementary workers who would accept an offer that pays 27 times more than their current job. These estimates likely reflect the occupational wage distribution: elementary occupations pay very little compared to professional ones.

The value of a certain job is not only in how much it pays but also what future wages it affords to its workers. The last three columns of Table 4.3 presents these values. High-skill jobs are more valuable: their full value is 19.5–20.8 times the magnitude of their flow utilities on average, while this multiplier is only 12.1–16.8 for low-skill jobs. These aggregate values are not a result of lower baseline flow utilities. The value of low-wage high-skill jobs are larger than the value of a high-wage elementary job, regardless of its enormous non-wage amenities. The same pattern holds in comparison with other low-skill jobs as well: high-skill jobs that pay in the lowest bin are roughly as valuable as well-paying low-skill jobs. These results highlight the importance of option values, with far-reaching dynamic implications.

4.2 Adding unobserved heterogeneity

I now introduce unobserved worker-specific heterogeneity to the model. That is, I distribute workers to two heterogeneity types and estimate the type distribution π, along with all

Figure 4.2: Aggregate type probabilities



Notes: Type probabilities by occupations in Appendix Figure E.6.

Figure 4.3: Offered wages

Notes: Type 1: solid lines. Type 2: dashed lines. Cumulative distribution functions and accepted wages in Appendix Figure E.8.

Table 4.4: Offer arrival and job separation rates with unobserved heterogeneity

Current occupation	Offer arrival rates								Job sep. rates	
	Type 1				*Type 2*					
	Total	Share			Total	Share			*Type 1*	*Type 2*
		Own	High	Low		Own	High	Low		
Managers	3.19	16.6	24.5	75.5	2.22	17.9	25.7	74.3	0.26	0.16
Professionals	4.63	13.7	31.5	68.5	3.20	15.0	33.1	66.9	0.29	0.17
Technicians	3.51	15.9	23.4	76.6	2.46	17.9	25.4	74.6	0.30	0.19
Commercial	1.29	46.0	7.7	92.3	0.96	48.8	7.2	92.8	0.54	0.29
Industry	0.98	55.1	5.0	95.0	0.89	65.3	3.9	96.1	0.44	0.23
Machine operators	2.12	31.6	5.2	94.8	1.54	34.9	4.8	95.2	0.41	0.24
Elementary	1.34	46.0	10.3	89.7	0.99	48.3	9.5	90.5	1.34	0.72
Out of labor force	0.85	–	12.2	87.8	1.06	–	13.4	86.6	–	–

Notes: Offer arrival rates: totals are annual rates; shares denote percentages of offers arriving from one's own/high-skill/low-skill occupations. Job separation rates: annual rates. All offer arrival rates in Appendix Figure E.9.

Table 4.5: Aggregate switching costs with unobserved heterogeneity

Current occupation	Switching costs					
	Type 1			*Type 2*		
	Own	High-skill	Low-skill	Own	High-skill	Low-skill
Managers	0.05	0.06	0.43	0.07	0.10	0.63
Professionals	0.05	0.04	0.60	0.08	0.06	0.83
Technicians	0.04	0.02	0.20	0.07	0.03	0.30
Commercial	0.08	0.17	1.04	0.12	0.24	1.38
Industry	0.02	0.85	0.24	0.03	1.16	0.34
Machine operators	0.03	1.86	0.41	0.05	2.37	0.57
Elementary	0.73	5.06	1.01	1.00	6.68	1.19
Out of labor force	–	0.67	0.34	–	0.46	0.23

Notes: Mean switching costs from one's current occupation to own/high-skill/low-skill occupations. All switching costs in Appendix Figure E.11.

Table 4.6: Flow utilities and option values with unobserved heterogeneity

Occupation	Flow utilities						Values					
	Type 1			*Type 2*			*Type 1*			*Type 2*		
	β	ψ_a	Comp. diff.	β	ψ_a	Comp. diff.	Full	Min	Max	Full	Min	Max
Managers	1.14	-1.78	0.14	1.46	-1.14	0.37	21.3	165.2	167.4	20.9	230.8	235.2
Professionals		-2.18	0.10		-1.43	0.30	22.6	166.2	168.1	21.6	232.5	235.9
Technicians		-1.42	0.19		-0.92	0.43	20.4	165.6	167.8	20.5	231.1	235.1
Commercial		0.80	1.34		0.55	1.18	15.8	163.2	165.3	17.9	227.9	232.3
Industry		0.97	1.56		0.65	1.26	15.6	164.0	166.4	17.9	229.5	234.5
Machine operators		0.46	1.00		0.31	1.00	16.5	164.9	167.4	18.4	229.8	234.5
Elementary		6.06	136.20		4.02	12.58	10.5	163.5	164.6	14.0	228.2	230.7
Out of the labor force		–	–		–	–	84.9	–	–	178.4	–	–

Notes: Compensating differentials: willingness-to-pay to switch to machine operating, relative to current wage. Full values: average of overall values normalized by flow utilities across wages in occupation. Min/max value: unnormalized values.

the type-specific structural parameters; see Appendix D for details about this estimation procedure.

The estimated types pick up stark differences across workers. Type 1 workers make up 64.3 percent of the sample while Type 2 makes up 35.7 percent. Figure 4.2 breaks down these overall figures by wage bins and shows that types separate low and high earners: workers in the lowest wage bin almost surely belong to Type 1 while those in the highest bin are Type 2. At the same time, the highest-wage workers in low-skill occupations belong to Type 2 with a 99.8 percent probability. These types apply to an uneven sample: while most Type 1 high-skilled workers earn below-median wages, they only make up 6 percent of the sample, compared to 59 percent of low-wage low-skilled workers. The contrast is even starker for low-skilled workers earning high wages: while they almost certainly belong to Type 2, they represent only 2 percent of the sample.

Unobserved heterogeneity reveals vastly different labor market landscapes across types. Starting with wage offers, Figure 4.3 attests that Type 2 workers receive higher wage offers than Type 1.[13] Type 2 high-skill occupations receive a lot more offers from high wages, especially professionals at 62 percent. Workers in low-skill occupations receive almost no offers from high wages, but offers to Type 2 workers bring about slightly higher pay than for Type 1 workers.

Unobserved heterogeneity types also affect the rates at which workers receive offers and separate from their jobs. Type 1 workers receive 35 percent more offers in both low- and high-skill occupations than Type 2 workers, as Table 4.4 demonstrates. However, a larger share of offers come from Type 2 workers' current occupation and other occupations of a similar skill content. At the same time, Type 1 workers separate more often from their jobs while Type 2 workers face more stable employment. These patterns suggest that Type 2 workers are more securely attached to the labor market but are also locked in to their current

[13]Even though Section 3 demonstrates that offered wages are flexibly identified, I impose additional parametrizations across types in the estimation. I model flexible wage offers for one type and shift them by a type-specific logit multiplier for the remaining types. See Appendix D for details.

occupations, relative to Type 1.

This lock-in pattern continues with the costs of switching. Type 2 workers face higher costs across the board, as shown in Table 4.5. Otherwise, the patterns are similar to those without unobserved heterogeneity: the least costly transitions are within one's current occupation, and transitions to occupations at another skill level are the most costly ones. Current high-skilled workers face lower costs to switch to low-skill occupations than the reverse. Within low-skill occupations, Type 2 workers face costs of 0.24–6.68 to switch to high-skill occupations, while Type 1 workers face 50 percent lower costs, ranging 0.20–0.60.

Preferences also exhibit this heterogeneity, as Table 4.6 illustrates. On one hand, Type 2 workers value wages more than Type 1, 1.46 compared to 1.14. On the other hand, Type 1 workers incur 50 percent larger non-wage amenities than Type 2 on average. Taken in tandem, the latter effect trumps the former: compensating differentials are more substantial for Type 1 than for Type 2 workers in absolute terms. Type 1 high-skilled workers would accept a machine operator offer for 10–19 percent of their current wage while this amount is 20 percentage points higher for Type 2 high-skilled workers. Similarly, Type 1 low-skilled workers would need much higher compensation than Type 2; e.g., Type 1 commercial workers require 14 percentage points higher wages than the 18 percent amount for Type 2 commercial workers.

A final piece demonstrating the effects of unobserved types on the results is the option values resulting from these estimates. Type 1 workers' values range between 20.4–22.6 times their flow utility in high-skill occupations and 10.5–16.5 in low-skill ones, whereas these figures are higher for Type 2 workers, 20.5–21.6 in high-skill and 14.0–18.4 in low-skill occupations. Curiously, the values of low-wage high-skill jobs are roughly equal to high-wage low-skill jobs for Type 1 workers, resembling earlier results without unobserved heterogeneity. However, for Type 2 workers high-wage jobs in low-skill occupations are unequivocally more valuable. These findings suggests that in early stages of one's career, being in a low-paying high-skill job is more beneficial; but as time goes by, being locked in to a low-skill

occupation yields higher value.

5 Life Cycle Wage Dynamics

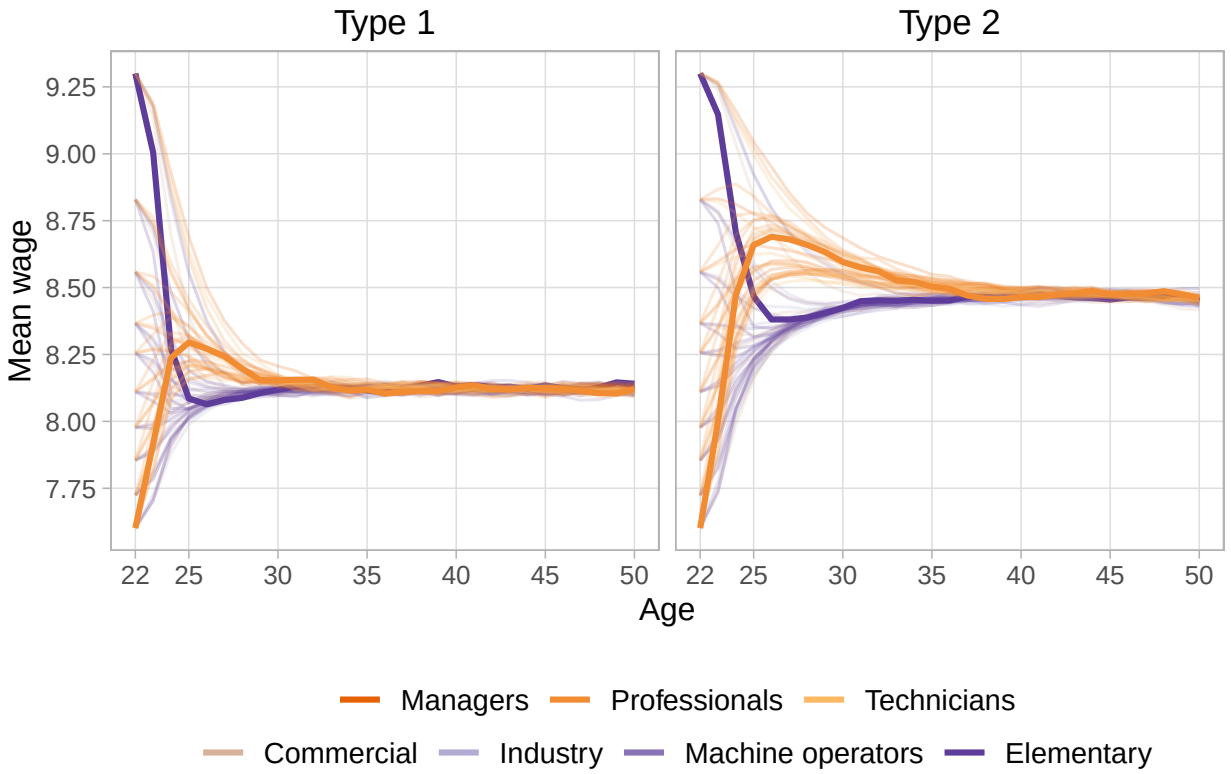
[In progress: decomposition with within-job wage promotions]

With the structural estimates at hand, this final section relates occupational mobility to the life cycle profile of wage inequality. I simulate careers starting from the empirical distribution of initial jobs, and compare wages at various points of the life cycle. I show that workers who start their careers in high-skill jobs have higher ex ante expected wages over their lifetime than low-skilled workers, regardless of their initial wage. Then I demonstrate that this occupational heterogeneity explains 96 percent of the empirical life cycle profile of wage inequality. Remarkably, the occupationally heterogeneous model fits the rapidly increasing wage inequality immediately upon entering the labor market. I find that heterogeneous offer arrival and job separation rates, flow utilities, and switching costs contribute equally to the explanatory power of occupations.

I start by demonstrating that occupations offer ex ante differing wage profiles, mirroring the descriptive evidence presented in Section 1. I simulate a large number of workers starting their careers at all possible wage levels in each occupation. Then I draw job spells from the competing hazard estimates and piece them together, thus creating lifetime careers. I record the occupational transitions and wage paths along these simulated careers. Finally, I compile ex ante wage profiles by averaging out these paths at each point of the life cycle.

Figure 5.1 shows these mean wage profiles by initial jobs in high- vs. low-skill occupations at all wage levels for each unobserved worker type. Specifically, the thick orange line tracks the ex ante expected wages of a 22 year old worker starting their career in a low-wage professional job. Similarly, the purple line follows the ex ante wage evolution of a 22 year old starting in a high-wage elementary job. Within three years, by age 25, the (initially) professional worker already expects to earn higher wages. The (initially) elementary worker

Figure 5.1: Ex ante wage profiles



Notes: Simulated wage profiles from baseline hazard estimates. Mean log wages by age across 2,500 simulations for each initial occupation-wage pair. Thick orange line: ex ante wage profile of a worker starting in a professional job in the lowest wage bin. Thick purple line: ex ante wage profile of a worker starting in an elementary job in the highest wage bin.

sharply loses their initial wage advantage: in expectation, they separate from their job and never catch up. These patterns are not unique to these two hypothetical workers: regardless of their initial wages, high-skilled workers (orange lines) always converge to the eventual steady-state mean from above while low-skilled workers (purple lines) converge from below.

Similar findings emerge for both unobserved types with some notable differences. Both types exhibit the same crossing pattern at age 25; however, the returns to high-skill occupations are higher and more persistent for Type 2 than for Type 1 workers. Wage paths for Type 1 workers converge to the same, lower mean by age 30 while convergence to a 42 percent higher mean happens slower, by age 38, for Type 2 workers.

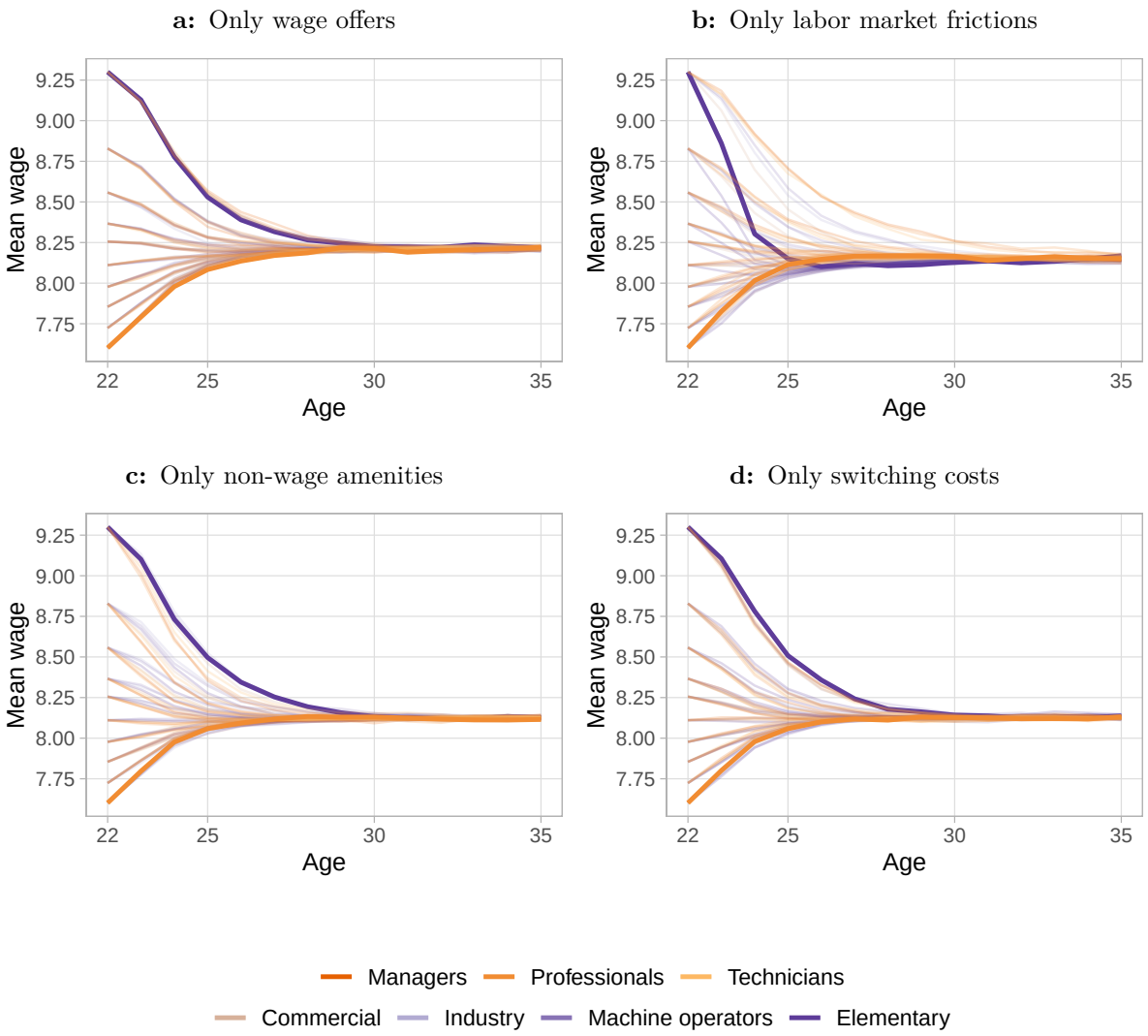
Which source of heterogeneity drives these patterns? I answer this question by repeating

the above simulation for a number of auxiliary models that incorporate only one heterogeneity source at a time. I estimate a version of the baseline model that features only occupation-specific wage offers. A second variant incorporates only labor market frictions through occupationally heterogeneous offer arrival and job separation rates. A third version models only occupation-specific non-wage amenities. A final fourth variant allows only costs of switching to vary across workers' current and offered occupations.

Figure 5.2 suggests that labor market frictions are the key determinant of the ex ante wage patterns:[14] the top right panel resembles the overall paths in Figure 5.1 the closest. Labor market frictions result in faster wage growth for workers in high-skill occupations and sharper wage drops for workers in low-skill occupations. Figure 5.3 shows that heterogeneous offer arrivals induce the rising patterns while job separations underlie expected wage drops. However, labor market frictions alone cannot account for the magnitude of the overall expected wage premium for workers starting in high-skill occupations: the gap between the orange and purple lines are nowhere near as wide. This high premium stems from the other occupational sources. In isolation, occupation-specific wage offers induce slightly higher expected wages for initially high-skilled workers: even though they receive higher-paying offers, fixed acceptance behavior across occupations results in similar paths. Heterogeneous non-wage amenities create slightly more dispersion across the ex ante wage paths, but in the opposite direction for higher wages. Workers who start in high-paying low-skill jobs incur the highest flow utility, high wages and high non-wage amenities, and hold onto these jobs. Similarly paid high-skilled workers, however, are more likely to leave to jobs with lower pay but overall higher non-wage amenities. Therefore, the purple lines on the top converge to the steady-state mean slower. The flipside of this logic applies to initially low-wage workers: those in low-wage, low-skill jobs will not receive wage offers that are high enough to offset their high non-wage amenities. Therefore the purple lines on the bottom converge to the

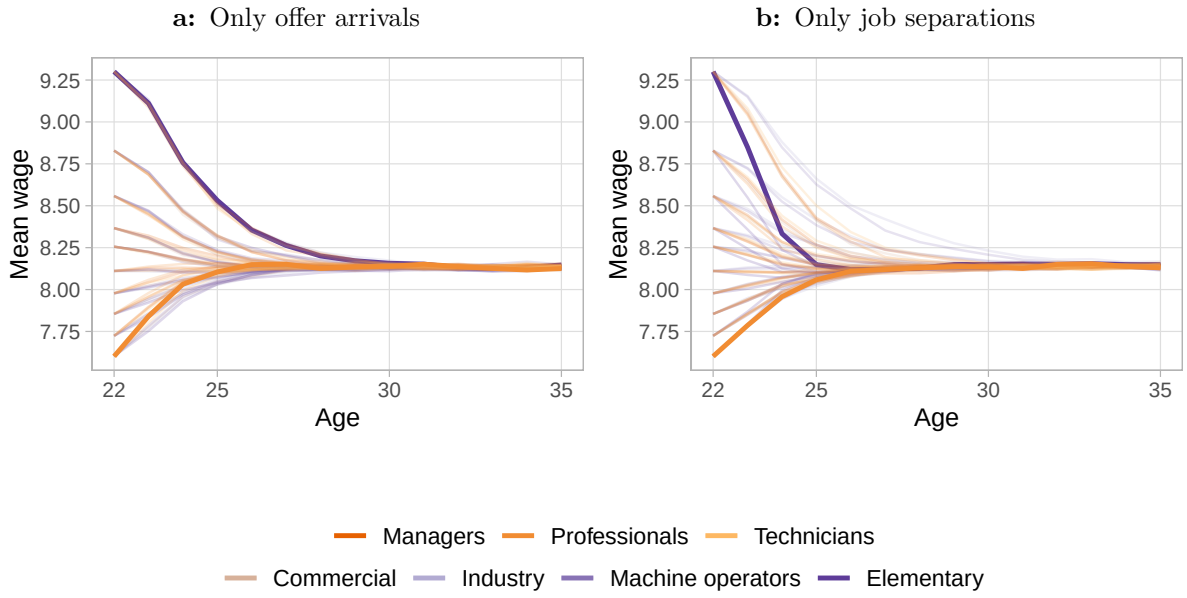
[14] I report results without unobserved heterogeneity for brevity: see Appendix Figure E.12 for two-type results. Furthermore, I zoom in on early career stages and only show ex ante wage paths until age 35—wages are similar in expectation afterwards.

Figure 5.2: Ex ante wage profiles by heterogeneity source



Notes: Simulated wage profiles from auxiliary hazard estimates. Mean log wages by age across 2,500 simulations for each initial occupation-wage pair. Thick orange line: ex ante wage profile of a worker starting in a professional job in the lowest wage bin. Thick purple line: ex ante wage profile of a worker starting in an elementary job in the highest wage bin. Results with unobserved heterogeneity in Appendix Figure E.12.

Figure 5.3: Ex ante wage profiles by heterogeneous labor market frictions



Notes: Simulated wage profiles from auxiliary hazard estimates. Mean log wages by age across 2,500 simulations for each initial occupation-wage pair. Thick orange line: ex ante wage profile of a worker starting in a professional job in the lowest wage bin. Thick purple line: ex ante wage profile of a worker starting in an elementary job in the highest wage bin.

steady-state mean slower. Finally, switching costs alone imply similarly slower convergence for low-skill occupations, as they face higher overall non-pecuniary costs to switch jobs.

Next, I link these diverging wage profiles to the life cycle profile of wage inequality. I repeat the simulation procedure outlined above, but instead of a hypothetical starting distribution, I start from the empirical distribution of jobs at age 22. Then, just like before, I draw and piece together job spells, thus creating lifetime careers from age 22 to 50. I record the occupational transitions and wage paths along these simulated careers. Finally, I calculate the within-group variance across paths at each age, by initial jobs. I repeat this exercise for estimates of the four restricted models, as well as an occupationless benchmark which shuts down all sources of occupational heterogeneity.

Table 5.1 contrasts the life cycle profiles of wage inequality in these alternative model specifications to the empirical life cycle wage dispersion. Overall, the full model fits 94

Table 5.1: Fitting the life cycle profile of wage inequality

Estimates	**Overall fit** (percent)	**Variance at various ages** (log points)			
		22	25	30	35
Data	–	0.152	0.294	0.363	0.343
Full model with all sources	94.3	0.152	0.273	0.313	0.323
Occupationless benchmark	65.6	0.152	0.182	0.212	0.223
Only wage offers	103.0	0.152	0.306	0.343	0.345
Only labor market frictions	90.4	0.152	0.268	0.303	0.305
Only non-wage amenities	86.2	0.152	0.261	0.294	0.290
Only switching costs	86.3	0.152	0.265	0.286	0.287

Notes: Overall fit: variance of simulated log wages divided by variance of log wages in data, age 25–50. Variance of log wages by age across simulated careers from empirical distribution of initial jobs. See Appendix Table E.1 for BIC measures of model fit.

percent of the observed inequality of wages, and closely matches the sharp increase in the inequality profile. The occupationless benchmark, with no occupational heterogeneity in its dispersion-generating sources, cannot compete with this fit: it only matches 63 percent of the total variation, and almost none of the increase early in the life cycle. Looking at all mechanisms in isolation, each of them improves the occupationless benchmark significantly, to the point that on their own they match most of the empirical dispersion. In fact, occupation-specific wage offers generate slightly higher dispersion than the data.[15] Labor market frictions account for 90 percent of the variation in isolation, while non-wage amenities and non-pecuniary job switching costs account for 86 percent each on their own. These results indicate that occupational heterogeneity in the sources of wage inequality is instrumental to account for the data patterns.

This accounting exercise is inspired by Taber and Vejlin (2020) but is conceptually different. Taber and Vejlin (2020) arbitrates between various sources of wage dispersion by shutting down each model mechanisms sequentially and measuring the drop in model fit at each exclusion. In contrast, I incorporate occupational heterogeneity in these mechanisms: therefore I do not exclude sources of dispersion, I only restrict them to be homogeneous across occupations. The occupationless benchmark in this paper can be thought of as the

[15]These estimates fit the data poorly, as Appendix Table E.1 shows.

conceptual equivalent to the full model in Taber and Vejlin (2020); however, their full model provides a better fit than the occupationless benchmark as they consider a different set of model mechanisms.[16] Instead, the focus of my paper is to shed light on the importance of occupational heterogeneity *within* the mechanisms themselves. Incorporating occupational heterogeneity to a wider range of mechanisms that lead to wage inequality is an important and interesting avenue for future research.

6 Conclusion

This paper argues that occupational mobility plays a key role in explaining the inequality of wages over the life cycle. I unfold this argument in four steps. First, I document that high-skill occupations offer steep wage growth to early-career workers while low-skill occupations feature flat wage profiles. Second, I build a structural model of mobility which incorporates occupational heterogeneity to several well-studied mechanisms behind wage inequality. Third, I estimate the model using Hungarian administrative data that follow workers' occupational histories and I uncover substantial occupational heterogeneity in its mechanisms. Fourth, I show that the occupational heterogeneity of these mechanisms is essential to account for life cycle wage dynamics.

I gain insights from a model of job transitions which attributes wage inequality to occupation-specific wage offers, labor market frictions, compensating differentials, and non-pecuniary costs of job switching. In the model, workers are employed in one of numerous occupations and incur utility from their wage and non-wage amenities. At any given instance, they may receive a job offer from another occupation and wage level; once an offer arrives, they decide whether to accept it. Their decision is shaped by comparing the value of their current job to the counterfactual value they would incur, should they accept the offer, as well as a non-pecuniary cost associated with switching jobs.

[16] In their full model, wage inequality results from heterogeneous skills prior to entering the labor market, firm type-specific offer arrivals, non-wage amenities, and human capital accumulation; furthermore, the equilibrium wage distribution results from bargaining between workers and firms.

I estimate the structural model on linked data compiled from Hungarian administrative records. These rich data have several main advantages over other, commonly used datasets; most importantly, they approximate the date of employer and occupational transitions, and they contain administrative information on workers' occupations, which map into skill levels. To estimate the model, I express its parameters in terms of the probability of accepting a job offer from any occupation that pays a certain wage, conditional on the current occupation and wage of the worker.

Taking my model to the data, I document that occupations that are associated with high skill levels (such as professionals or technicians) offer higher wages than low-skill occupations (e.g., machine operators and industry occupations). Job offers from high-skill occupations arrive more frequently than low-skill offers, especially to high-skilled workers, while low-skill occupations have more frequent job separations. Workers in low-skill occupations face large non-pecuniary costs to switch to high-skill occupations. Furthermore, compensating differentials for workers in low-skill occupations are substantially larger than for those in high-skill occupations, locking in these workers to lower wage trajectories. Even though low-skill occupations offer high flow values from non-wage amenities, high-skill occupations are more valuable overall as they have higher option values.

Lastly, I link these structural estimates to wage inequality over the life cycle. I calculate the ex ante expected wage profiles of workers starting their careers in any possible occupation-wage combination. The full model gives rise to crossing wage paths: workers who start in low-wage high-skill jobs experience rapid wage growth, while those starting in high-wage low-skill jobs quickly lose their initial wage gains. Separating each model mechanism, I show that these wage dynamics result mainly from occupational labor market frictions. However, all other mechanisms—occupational wage offers, non-wage amenities, switching costs—are required to fully account for the empirical dispersion of wages.

I conclude this paper with a remark on avenues for future research. Discerning the occupational sources of wage inequality has important policy implications: occupational

heterogeneity can point out precise targets for policy interventions. For example, if inequality stems from large frictions or switching costs from a low-skill occupation to a high-skill one, targeted policies should reduce frictions or subsidize transition costs across them. More research is needed for such policy recommendations because workers, and especially firms, may respond to interventions in ways that are not modeled here. This paper takes the first step towards these precise recommendations by demonstrating the scope for such targeted policies.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), 251–333.

Aguirregabiria, V. and P. Mira (2010). Dynamic Discrete Choice Structural Models: A Survey. *Journal of Econometrics 156*(1), 38–67.

Antonovics, K. and L. Golan (2012). Experimentation and Job Choice. *Journal of Labor Economics 30*(2), 333–366.

Arcidiacono, P. and P. B. Ellickson (2011). Practical Methods for Estimation of Dynamic Discrete Choice Models. *Annual Review of Economics 3*(1), 363–394.

Arcidiacono, P., A. Gyetvai, A. Maurel, and E. Jardim (2022). Identification and Estimation of Continuous-Time Job Search Models with Preference Shocks. NBER Working Paper 30655.

Arcidiacono, P., V. J. Hotz, A. Maurel, and T. Romano (2020). *Ex Ante* Returns and Occupational Choice. *Journal of Political Economy 128*(12), 4475–4522.

Arcidiacono, P. and R. A. Miller (2011). Conditional Choice Probability Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity. *Econometrica 79*(6), 1823–1867.

Ashworth, J., V. J. Hotz, A. Maurel, and T. Ransom (2021). Changes Across Cohorts in Wage Returns to Schooling and Early Work Experiences. *Journal of Labor Economics 39*(4), 931–964.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2014). Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics. *American Economic Review 104*(6), 1551–1596.

Bagger, J. and R. Lentz (2019). An Empirical Model of Wage Dispersion with Sorting. *Review of Economic Studies 86*(1), 153–190.

Bayer, C. and M. Kuhn (2023). Job Levels and Wages. IZA Discussion Paper 16177.

Bonhomme, S., T. Lamadon, and E. Manresa (2019). A Distributional Framework for Matched Employer Employee Data. *Econometrica 87*(3), 699–739.

Burdett, K., C. Carrillo-Tudela, and M. G. Coles (2011). Human Capital Accumulation and Labor Market Equilibrium. *International Economic Review 52*(3), 657–677.

Burdett, K. and D. T. Mortensen (1998). Wage Differentials, Employer Size, and Unemployment. *International Economic Review 39*(2), 257–273.

Busch, C. (2020). Occupational Switching, Tasks, and Wage Dynamics. Working Paper.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin (2006). Wage Bargaining with On-the-job Search: Theory and Evidence. *Econometrica 74*(2), 323–364.

Card, D. (1999). The Causal Effect of Education on Earnings. In *Handbook of Labor Economics*, Volume 3, pp. 1801–1863. Elsevier Masson SAS.

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics 36*(S1), S13–S70.

Card, D., J. Heining, and P. Kline (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics 128*(3), 967–1015.

Carrillo-Tudela, C. and L. Visschers (2023). Unemployment and Endogenous Reallocation over the Business Cycle. *Econometrica 91*(3), 1119–1153.

Cox, D. R. (1959). The Analysis of Exponentially Distributed Life-Times with Two Types of Failure. *Journal of the Royal Statistical Society 21*(2), 411–421.

Cox, D. R. (1962). *Renewal Theory*. Methuen and Co.

DellaVigna, S., A. Lindner, B. Reizer, and J. F. Schmieder (2017). Reference-dependent Job Search: Evidence from Hungary. *Quarterly Journal of Economics 132*(4), 1969–2018.

Groes, F., P. Kircher, and I. Manovskii (2015). The U-Shapes of Occupational Mobility. *Review of Economic Studies 82*(2), 659–692.

Hotz, V. J. and R. A. Miller (1993). Conditional Choice Probabilities and the Estimation of Dynamic Models. *Review of Economic Studies 60*(3), 497–529.

Jarosch, G. (2023). Searching for Job Security and the Consequences of Job Loss. *Econometrica 91*(3), 903–942.

Jolivet, G., F. Postel-Vinay, and J.-M. Robin (2006). The Empirical Content of the Job Search Model: Labor Mobility and Wage Distributions in Europe and in the US. *European Economic Review 50*(4), 877–907.

Juhn, C., K. M. Murphy, and B. Pierce (1993). Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy 101*(3), 410–442.

Kambourov, G. and I. Manovskii (2009a). Occupational Mobility and Wage Inequality. *Review of Economic Studies 76*(2), 731–759.

Kambourov, G. and I. Manovskii (2009b). Occupational Specificity of Human Capital. *International Economic Review 50*(1), 63–115.

Keane, M. P. and K. I. Wolpin (1997). The Career Decisions of Young Men. *Journal of Political Economy 105*(3), 473–522.

Lise, J., C. Meghir, and J.-M. Robin (2016). Matching, Sorting and Wages. *Review of Economic Dynamics 19*(1), 63–87.

Llull, J. and R. A. Miller (2018). Internal Migration and Work Experience in Dual Labor Markets. Working Paper.

McCall, B. P. (1990). Occupational Matching: A Test of Sorts. *Journal of Political Economy 98*(1), 45–69.

Miller, R. A. (1984). Job Matching and Occupational Choice. *Journal of Political Economy 92*(6), 1086–1120.

Neal, D. (1999). The Complexity of Job Mobility among Young Men. *Journal of Labor Economics 17*(2), 237–261.

Pilossoph, L. (2014). Sectoral Shocks and Move Unemployment. Working Paper.

Postel-Vinay, F. and J.-M. Robin (2002). Equilibrium Wage Dispersion with Worker and Employer Heterogeneity. *Econometrica 70*(6), 2295–2350.

Rosen, S. (1986). The Theory of Equalizing Differences. In *Handbook of Labor Economics*, Volume 1, Chapter 12, pp. 641–692.

Siow, A. (1984). Occupational Choice Under Uncertainty. *Econometrica 52*(3), 631–645.

Sorkin, I. (2018). Ranking Firms Using Revealed Preference. *Quarterly Journal of Economics 133*(3), 1331–1393.

Sullivan, P. (2010). A Dynamic Analysis of Educational Attainment, Occupational Choices, and Job Search. *International Economic Review 51*(1), 289–317.

Sullivan, P. and T. To (2014). Search and Non-wage Job Characteristics. *Journal of Human Resources 49*(2), 472–507.

Taber, C. and R. Vejlin (2020). Estimation of a Roy/Search/Compensating Differential Model of the Labor Market. *Econometrica 88*(3), 1031–1069.

Tsiatis, A. (1975). A Nonidentifiability Aspect of the Problem of Competing Risks. *Proceedings of the National Academy of Sciences 72*(1), 20–22.

Wiczer, D. (2015). Long-term Unemployment: Attached and Mismatched? Federal Bank of St. Louis Research Division Working Paper 2015-042A.

Appendices

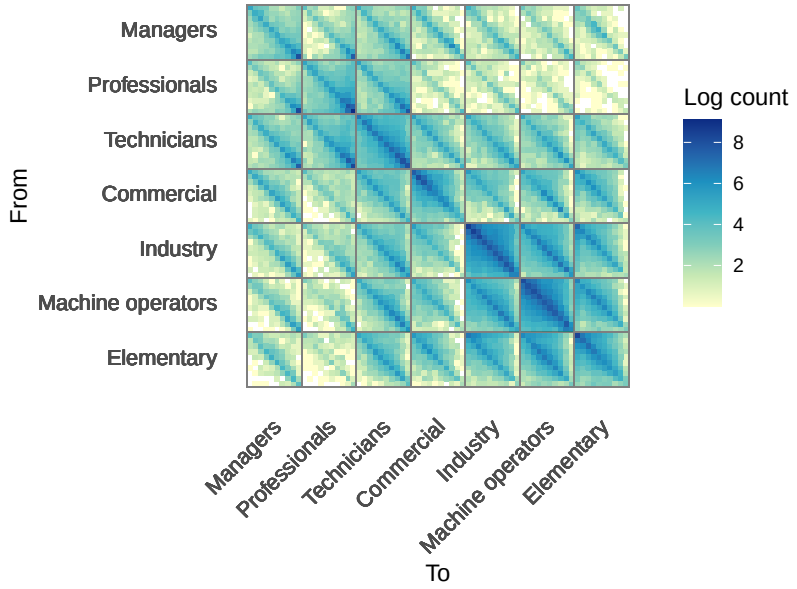
A Data

This appendix contains additional information on the Hungarian administrative data. Back to Section 1.

Job-to-job transition matrix

Each block represents transitions across occupations and, due to the occupation classification system, the skill content of occupations is loosely decreasing left-to-right and bottom-to-top. Furthermore, wages within each block are increasing left-to-right and bottom-to-top; therefore, within blocks the diagonal represents transitions which do not involve a wage change, above the diagonal are wage cuts and under it are wage bumps. The overwhelming majority of occupation blocks contain at least one transition; the further the jump in terms of occupational skill content, the more likely empty cells occur. Many transitions happen at the same occupation and a similar wage rate, implying only a firm switch. Furthermore, conditional on an occupation switch (i.e., in off-diagonal blocks) wages are more likely to stay at their previous level.

Appendix Figure A.1: Number of observations by transition cells



Notes: Log number of transitions in each origin and destination occupation-wage pair. Within each occupation-to-occupation block, wages are increasing left-to-right and bottom-to-top. White cells are empty.

Appendix Table A.1: Skill content of occupations

Occupation	Skill level	Educational requirement
Managers	5	College or post-secondary specialist ed.
Professionals	4	College
Technicians	3	Post-secondary specialist ed.
Commercial	2	Secondary ed.
Industry	2	Secondary ed.
Machine operators	2	Secondary ed.
Elementary	1	No formal qualifications

B Model

This appendix provides more details of the model of job mobility within and across occupations. Back to Section 2.

B.1 Stochastic switching costs interpreted as preference shocks

I assume that switching costs are ex ante unknown and drawn from a known distribution upon the arrival of job offers, which underlies the dispersion in offer acceptance even among observably equivalent workers. From the model's perspective, this assumption is equivalent to having fixed switching costs and a preference shock associated with the offer. To see this, rewrite Equation 2.1 as

$$\left(\sum_o \lambda_a^o + \sum_w \chi_{ai}^{aw} + \delta_a + \rho\right) V_{ai} = u_{ai} + \sum_w \chi_{ai}^{aw} V_{aw} + \delta_a V_n + \sum_o \lambda_a^o \, \mathbb{E}_{w,\varepsilon} \max\left[V_{ow} - c_a^o + \varepsilon, V_{ai}\right]. \tag{B.1}$$

Here ε is a preference shock, drawn when a job offer arrives. Assuming that ε is logistically distributed with mean zero is equivalent to the distributional assumption above.

In terms of interpretation, stochastic switching costs depict ex ante uncertainty regarding amenities associated with transitioning from occupation a to b. A negative cost realization may be interpreted as a desirable amenity the worker is willing to pay for. On the other hand, preference shocks may be interpreted as ex ante unknown non-pecuniary aspects of the job offer. These seemingly competing interpretations are, in fact, interchangeable.

B.2 Value functions expressed in terms of CCPs

From Equation 2.1,

$$\begin{aligned}\Big(\sum_o \lambda_a^o + \sum_w \chi_{ai}^{aw} + \delta_a + \rho\Big)V_{ai} &= u_{ai} + \sum_w \chi_{ai}^{aw} V_{aw} + \delta_a V_n + \sum_o \lambda_a^o \, \mathbb{E}_{w,\tilde{c}} \max\left[V_{ow} - \tilde{c}_a^o, V_{ai}\right] \\ &= u_{ai} + \sum_w \chi_{ai}^{aw} V_{aw} + \delta_a V_n + \sum_o \lambda_a^o \, \mathbb{E}_{w,\tilde{c}} \left\{V_{ai} + \max\left[V_{ow} - V_{ai} - \tilde{c}_a^o, 0\right]\right\} \\ \rho V_{ai} &= u_{ai} + \sum_w \chi_{ai}^{aw} (V_{aw} - V_{ai}) + \delta_a (V_n - V_{ai}) + \sum_o \lambda_a^o \, \mathbb{E}_{w,\tilde{c}} \max\left[V_{ow} - V_{ai} - \tilde{c}_a^o, 0\right]\end{aligned}$$

Since $\tilde{c}_a^o \sim \text{Logistic}(c_a^o)$, the Emax term can be expressed as

$$\mathbb{E}_{w,\tilde{c}} \max\left[V_{ow} - V_{ai} - \tilde{c}_a^o, 0\right] = \mathbb{E}_w \left\{\log\left(1 + \exp(V_{ow} - V_{ai} - c_a^o)\right)\right\}.$$

Now note that the log term looks eerily similar to the probability to reject an offer (c.f. Equation 2.5):

$$1 - p_{ai}^{ow} = \frac{1}{1 + \exp\left(V_{ow} - V_{ai} - c_a^o\right)}.$$

Plugging this back to the value function yields

$$\rho V_{ai} = u_{ai} + \sum_w \chi_{ai}^{aw} (V_{aw} - V_{ai}) + \delta_a (V_n - V_{ai}) + \sum_o \lambda_a^o \, \mathbb{E}_w\{-\log(1 - p_{ai}^{ow})\}.$$

Finally, integrating out the offered wage p.m.f. yields Equation 2.3:

$$\rho V_{ai} = u_{ai} + \sum_w \chi_{ai}^{aw} (V_{aw} - V_{ai}) + \delta_a (V_n - V_{ai}) - \sum_{o,w} \lambda_a^o \log(1 - p_{ai}^{ow}) f^{ow}.$$

The same logic applies to the value of non-employment.

C Identifying Structural Parameters

This mathematical appendix discusses further details of the constructive identification of the structural parameters. Back to Section 3.

Offer arrival rates within occupations: From Equation 3.7,

$$\varpi_{ai}^{aj} + \varpi_{aj}^{ai} = \varpi_{ak}^{a\ell} + \varpi_{a\ell}^{ak} \tag{C.1}$$

$$\frac{h_{ai}^{aj}}{\lambda_a^a f^{aj} - h_{ai}^{aj}} \frac{h_{aj}^{ai}}{\lambda_a^a f^{ai} - h_{aj}^{ai}} = \frac{h_{ak}^{a\ell}}{\lambda_a^a f^{a\ell} - h_{ak}^{a\ell}} \frac{h_{a\ell}^{ak}}{\lambda_a^a f^{ak} - h_{a\ell}^{ak}} \tag{C.2}$$

Therefore

$$\lambda_a^a = \frac{\left[h_{ai}^{aj} f^{ai} + h_{aj}^{ai} f^{aj}\right] h_{ak}^{a\ell} h_{a\ell}^{ak} - \left[h_{ak}^{a\ell} f^{ak} + h_{a\ell}^{ak} f^{a\ell}\right] h_{ai}^{aj} h_{aj}^{ai}}{f^{ai} f^{aj} h_{ak}^{a\ell} h_{a\ell}^{ak} - f^{ak} f^{a\ell} h_{ai}^{aj} h_{aj}^{ai}} \tag{C.3}$$

Offer arrival rates across occupations: From Equation 3.10,

$$\begin{pmatrix} \varpi_{ai}^{bj} + \varpi_{bj}^{ai} \\ \varpi_{ai'}^{bj'} + \varpi_{bj'}^{ai'} \end{pmatrix} = \begin{pmatrix} \varpi_{ak}^{b\ell} + \varpi_{b\ell}^{ak} \\ \varpi_{ak'}^{b\ell'} + \varpi_{b\ell'}^{ak'} \end{pmatrix} \tag{C.4}$$

$$\begin{pmatrix} \frac{h_{ai}^{bj}}{\lambda_a^b f^{bj} - h_{ai}^{bj}} \frac{h_{bj}^{ai}}{\lambda_b^a f^{ai} - h_{bj}^{ai}} \\ \frac{h_{ai'}^{bj'}}{\lambda_a^b f^{bj'} - h_{ai'}^{bj'}} \frac{h_{bj'}^{ai'}}{\lambda_b^a f^{ai'} - h_{bj'}^{ai'}} \end{pmatrix} = \begin{pmatrix} \frac{h_{ak}^{b\ell}}{\lambda_a^b f^{b\ell} - h_{ak}^{b\ell}} \frac{h_{b\ell}^{ak}}{\lambda_b^a f^{ak} - h_{b\ell}^{ak}} \\ \frac{h_{ak'}^{b\ell'}}{\lambda_a^b f^{b\ell'} - h_{ak'}^{b\ell'}} \frac{h_{b\ell'}^{ak'}}{\lambda_b^a f^{ak'} - h_{b\ell'}^{ak'}} \end{pmatrix} \tag{C.5}$$

The arrival rates $(\lambda_a^b, \lambda_b^a)'$ are the solution to this system of equations; analytically,

$$\lambda_a^b = \frac{A_2 B_3 - A_3 B_2}{A_2 B_1 - A_1 B_2} \qquad \text{and} \quad \lambda_b^a = \frac{A_3 B_2 - A_2 B_3}{A_3 B_1 - A_1 B_3} \tag{C.6}$$

where

$$A_1 = f^{b\ell} f^{ak} h^{bj}_{ai} h^{ai}_{bj} - f^{bj} f^{ai} h^{b\ell}_{ak} h^{ak}_{b\ell}, \qquad B_1 = f^{b\ell'} f^{ak} h^{bj'}_{ai'} h^{ai'}_{bj'} - f^{bj'} f^{ai'} h^{b\ell'}_{ak'} h^{ak'}_{b\ell'},$$

$$A_2 = f^{b\ell} h^{ak}_{b\ell} h^{bj}_{ai} h^{ai}_{bj} - f^{bj} h^{ai}_{bj} h^{b\ell}_{ak} h^{ak}_{b\ell}, \qquad B_2 = f^{b\ell'} h^{ak'}_{b\ell'} h^{bj'}_{ai'} h^{ai'}_{bj'} - f^{bj'} h^{ai'}_{bj'} h^{b\ell'}_{ak'} h^{ak'}_{b\ell'},$$

$$A_3 = f^{ak} h^{b\ell}_{ak} h^{bj}_{ai} h^{ai}_{bj} - f^{ai} h^{bj}_{ai} h^{b\ell}_{ak} h^{ak}_{b\ell}, \qquad B_3 = f^{ak'} h^{b\ell'}_{ak'} h^{bj'}_{ai'} h^{ai'}_{bj'} - f^{ai'} h^{bj'}_{ai'} h^{b\ell'}_{ak'} h^{ak'}_{b\ell'}.$$

D Estimation Procedure

It is useful to denote non-employment spells as an additional job type in this appendix.[17] Let (o, w) denote a generic job in occupation o and wage w as before: a "job" in non-employment is denoted by $(n, 0)$.

The data contain information on I individuals, indexed by ι, with S_ι spells each. I observe three sets of information for each individual ι. First, I observe their first job—i.e., their initial occupation and wage rate $(\underline{o}_\iota, \underline{\mathrm{w}}_\iota)$.[18] Second, for each spell $s \in \{1, \ldots, S_\iota\}$ I observe its duration t_s, the occupation and wage rate of the origin job (a_s, i_s), the transition type d_s (for employment spells, either a wage transition WW, a job transition EE, exiting the labor force EN, or right-censoring RC; for non-employment spells, either (re-)entering the labor force NE or right-censoring RC), and the occupation and wage rate of the destination job (b_s, j_s). That is, I observe $\{\underline{y}_\iota, \underline{o}_\iota, \underline{\mathrm{w}}_\iota, \{t_s, a_s, \mathrm{i}_s, d_s, b_s, \mathrm{j}_s\}_{s \in S_\iota}\}$ for all $\iota \in \{1, \ldots, I\}$. Further, I assume that individuals can belong to one of R unobserved types, indexed by r, with probability π_r. (I set $R = 2$.) The full loglikelihood of observing these data is

$$\sum_\iota \log \left(\sum_r \pi_r L_{\iota r} \right), \tag{D.1}$$

where $L_{\iota r}$ stands for the likelihood contribution of individual ι of type r.

I implement a reduced version of the EM algorithm (cf. Arcidiacono and Miller, 2011; Arcidiacono, Gyetvai, Maurel, and Jardim, 2022). This implementation alleviates the need to iterate the E and M steps of the algorithm. First, I estimate the posterior type distribution by maximizing a reduced-form variant of the full loglikelihood and calculate the conditional type probabilities $q_{\iota r}$. Second, I estimate the model parameters by maximizing the expected complete loglikelihood given $q_{\iota r}$.

[17] Back to the results in Section 4.

[18] Wage rates here are continuous real wage levels, not discrete wage bins that are used in the model. $\log \mathrm{i}_s = 0$ for non-employment spells.

D.1 Posterior type distribution

I estimate the posterior type distribution by maximizing the reduced-form full loglikelihood

$$\sum_{\iota} \log \left[\sum_{r} \pi_r \left(\underline{L}_{\iota r} \prod_{s} \tilde{L}_{sr} \right) \right]. \tag{D.2}$$

$\left(\underline{L}_{\iota r} \prod_s \tilde{L}_{sr} \right)$ is a reduced-form version of $L_{\iota r}$ in Equation D.1. $\underline{L}_{\iota r}$ is the likelihood contribution of initial observations, constructed as

$$\underline{L}_{\iota r} = \frac{\exp(\sum_o \mathbb{1}(\underline{o}_\iota = o)\underline{\gamma}_{1o} + \underline{\gamma}_2 \log \underline{\mathrm{w}}_\iota + \underline{\gamma}_{3r})}{\sum_o \exp(\underline{\gamma}_{1o} + \underline{\gamma}_2 \log \underline{\mathrm{w}}_\iota + \underline{\gamma}_{3r})} \times \frac{1}{\underline{\sigma}} \phi \left(\frac{\log \underline{\mathrm{w}}_\iota - \sum_o \mathbb{1}(\underline{o}_\iota = o)\underline{\gamma}_{4o} - \underline{\gamma}_{5r}}{\underline{\sigma}} \right) \tag{D.3}$$

where $\phi(\cdot)$ denotes the standard normal p.d.f. and $\underline{\gamma}_{11} = 0$. This specification solves the initial conditions problem posed by the dependence of initial jobs on unobserved individual types.

$\tilde{L}_{sr}$ is the likelihood contribution of each spell s of a type r individual ι, which consists of three parts: (i) the contribution of hazards of moving to any new job, constructed as

$$\tilde{h}_{sr} = \exp \left(\sum_a \mathbb{1}(a_s = a)\tilde{\gamma}_{1a} + \tilde{\gamma}_2 \log \mathrm{i}_s + \tilde{\gamma}_{3r} \right), \tag{D.4}$$

(ii) the contribution of new occupations, and (iii) the contribution of new wages. All of these contributions are conditional on the current occupation and wage. The three parts together

yield[19]

$$\begin{aligned}\tilde{L}_{sr} = \tilde{h}_{sr}^{\mathbb{1}(d_s \in \{EE,NE\})} \exp(-\tilde{h}_{sr}\, t_s) \\ \times \Bigg[\frac{\exp(\sum_a \mathbb{1}(a_s = a)\tilde{\gamma}_{4a} + \tilde{\gamma}_5 \log \mathrm{i}_s + \tilde{\gamma}_6 \mathbb{1}(d_s = NE) + \sum_b \mathbb{1}(b_s = b)\tilde{\gamma}_{7b} + \tilde{\gamma}_{8r})}{\sum_{a,b} \exp(\tilde{\gamma}_{4a} + \tilde{\gamma}_5 \log \mathrm{i}_s + \tilde{\gamma}_6 \mathbb{1}(d_s = NE) + \tilde{\gamma}_{7b} + \tilde{\gamma}_{8r})} \\ \times \frac{1}{\tilde{\sigma}} \phi \left(\frac{\log \mathrm{j}_s - \sum_a \mathbb{1}(a_s = a)\tilde{\gamma}_{9a} - \tilde{\gamma}_{10} \log \mathrm{i}_s - \tilde{\gamma}_{11} \mathbb{1}(d_s = NE) - \tilde{\gamma}_{12,r}}{\tilde{\sigma}} \right) \Bigg]^{\mathbb{1}(d_s \in \{EE,NE\})}\end{aligned} \tag{D.5}$$

where $\tilde{\gamma}_{41}$ is normalized to 0.

After maximizing the objective function in Equation D.2 w.r.t. $(\underline{\gamma}, \underline{\sigma}, \tilde{\gamma}, \tilde{\sigma}, \pi)$, I calculate the conditional type probabilities as

$$q_{\iota r} = \frac{\pi_r \left(\underline{L}_{\iota r} \prod_s \tilde{L}_{sr} \right)}{\sum_r \pi_r \left(\underline{L}_{\iota r} \prod_s \tilde{L}_{sr} \right)}. \tag{D.6}$$

D.2 Structural parameters

Given the conditional type probabilities, I estimate the parameters of the model in two steps. First, I estimate the within-job wage change rates χ and the job destruction rates δ. Second, I estimate the remaining parameters by maximizing the expected complete loglikelihood.

D.2.1 Within-job wage change rates and job destruction rates

The only choice individuals make in the model is to accept or reject job offers: wage changes and job separations are outside of their control. Therefore, without unobserved heterogeneity these parameters can be estimated directly from the data. With unobserved heterogeneity, the same calculations apply with the conditional type probabilities as weights. Specifically, the wage change rates are calculated as

$$(\hat{\chi}_{ai}^{aw})_r = \frac{\sum_\iota q_{\iota r} \sum_s \mathbb{1}(a_s = a, i_s = i, d_s = WW, j_s = w)}{\sum_\iota q_{\iota r} \sum_s \mathbb{1}(a_s = a, i_s = i)\, t_s} \tag{D.7}$$

[19]The term $\exp(-\tilde{h}_{sr}\, t_s)$ in Equation D.5 is the survival function associated with hazard $\tilde{h}_{sr}$.

while the job separation rates are calculated as

$$\left(\hat{\delta}_a\right)_r = \frac{\sum_\iota q_{\iota r} \sum_s \mathbb{1}(a_s = a, d_s = EN)}{\sum_\iota q_{\iota r} \sum_s \mathbb{1}(a_s = a)\, t_s} \tag{D.8}$$

for all $a \neq n$.[20]

D.2.2 Remaining parameters

I estimate the remaining parameters by maximizing the expected complete loglikelihood

$$\sum_\iota \sum_r q_{\iota r} \sum_s \log L_{sr}. \tag{D.9}$$

L_{sr} stands for the likelihood contribution of each spell s of a type r individual ι, constructed from the job-to-job hazards as[21]

$$L_{sr}(h_r) = \prod_{a,i} \prod_{b,j} \left[\left(h_{ai}^{bj}\right)_r^{\mathbb{1}(b_s=b, j_s=j)} \exp\left(-\left(h_{ai}^{bj}\right)_r t_s\right)\right]^{\mathbb{1}(a_s=a, i_s=i)}. \tag{D.10}$$

Note that the expected complete loglikelihood can be restructured as

$$\begin{aligned}
&\sum_\iota \sum_r q_{\iota r} \sum_s \log \left(\prod_{a,i} \prod_{b,j} \left[\left(h_{ai}^{bj}\right)_r^{\mathbb{1}(b_s=b, j_s=j)} \exp\left(-\left(h_{ai}^{bj}\right)_r t_s\right)\right]^{\mathbb{1}(a_s=a, i_s=i)} \right) \\
=&\sum_r \left(\sum_{a,i} \sum_{b,j} \log\left[\left(h_{ai}^{bj}\right)_r\right] \sum_\iota q_{\iota r} \sum_s \mathbb{1}(a_s = a, i_s = i)\mathbb{1}(b_s = b, j_s = j) \right. \\
&\left. - \sum_{a,i} \sum_{b,j} \left(h_{ai}^{bj}\right)_r \sum_\iota q_{\iota r} \sum_s \mathbb{1}(a_s = a, i_s = i)\, t_s \right),
\end{aligned} \tag{D.11}$$

which has two important implications. First, aggregate data alone (weighted by the q's) are sufficient to estimate the structural parameters. Second, the parameters can be estimated separately by unobserved types.

I impose the structure of the model on the hazards by substituting $h_{ai}^{bj} = \lambda_a^b f^{bj} p_{ai}^{bj}$ (Equa-

[20] Recall that non-employment spells are denoted as an additional job type in this appendix.
[21] Note that wages i_s, j_s are now discrete: they can be easily discretized from continuous observations.

tion 3.1, momentarily omitting types):

$$L_s(h) = L_s(\lambda f p). \tag{D.12}$$

λ and f are parameters to be estimated, p itself is a function of parameters. I back out p by iterating the value function to a fixed point within the routine: in the mth iteration,

$$\left(\sum_o \lambda_a^o + \sum_w \chi_{ai}^{aw} + \delta_a + \rho\right) V_{ai}^{(m)} = u_{ai} + \sum_o \lambda_a^o V_{ai}^{(m-1)} + \sum_w \chi_{ai}^{aw} V_{aw}^{(m-1)} + \delta_a V_n^{(m-1)} + \sum_{o,w} \lambda_a^o \log\left(1 + \exp\left(V_{ow}^{(m-1)} - V_{ai}^{(m-1)} - c_a^b\right)\right) f^{ow}. \tag{D.13}$$

From here, I calculate p as

$$p_{ai}^{bj} = \frac{\exp(V_{bj}^* - V_{ai}^* - c_a^b)}{1 + \exp(V_{bj}^* - V_{ai}^* - c_a^b)}. \tag{D.14}$$

That is, I express p in terms of the model parameters as $p = p(\lambda, f, u, c, \chi, \delta)$ and, in turn, the likelihood contribution as $L_s = L_s(\lambda f p(\lambda, f, u, c, \chi, \delta)) = L_s(\lambda, f, u, c, \chi, \delta)$.

Assembling all terms and adding types back to the notation, I maximize the expected complete loglikelihood in Equation D.9. The parameter estimates are

$$(\hat{\lambda}, \hat{f}, \hat{u}, \hat{c}) = \arg\max_{\lambda, f, u, c} \sum_\iota \sum_r q_{\iota r} \sum_s \log L_{sr}(\lambda, f, u, c, \hat{\chi}, \hat{\delta}). \tag{D.15}$$

D.2.3 Additional parametrizations

Offered wage distribution: I parametrize the distribution of offered wages in an ordered logit structure. I define wage cutoffs as[22]

$$\phi_w = \begin{cases} \theta_1^\phi & \text{for } w = 1 \\ \phi_{w-1} + \exp(\theta_2^\phi + \theta_3^\phi \log \mathrm{w}_w + \theta_4^\phi \log \mathrm{w}_w^2) & \text{for } w > 1 \end{cases}. \tag{D.16}$$

Then I define the distribution of offered wages as

$$f^{ow} = \begin{cases} \Lambda(\phi_w + \theta^o) & \text{for } w = 1 \\ \Lambda(\phi_w + \theta^o) - \Lambda(\phi_{w-1} + \theta^o) & \text{for } 1 < w < W \\ 1 - \Lambda(\phi_{W-1} + \theta^o) & \text{for } w = W \end{cases}, \tag{D.17}$$

where $\Lambda(\cdot)$ denotes the logistic function. θ^o is an occupation-specific logit shifter: as θ^o increases, the distribution shifts to the left.

D.3 The contribution of occupational mechanisms

I assess the contribution of the occupation-specific mechanisms by decomposing the likelihood of the full model. I use the Shapley–Owen–Shorrocks decomposition.[23]

Let L denote the expected complete likelihood of the model:

$$L(\lambda, f, u, c, \chi, \delta) = \sum_\iota \sum_r q_{\iota r} \sum_s \log L_{sr}(\lambda, f, u, c, \chi, \delta). \tag{D.18}$$

Each set of parameters can be heterogeneous within and across occupations—as in the full model—or fixed, in which case I omit them from the function argument. For example, $L(\lambda)$ denotes the model with only occupation-specific offer arrival rates and $L(\emptyset)$ denotes the

[22] Just like in Equation 3.22, w_w stands for the wage level associated with wage bin w.
[23] Thanks to Sergio Ocampo for suggesting this method.

occupationally homogeneous model. The contribution of mechanism m is, then,

$$C_m = \sum_{k=0}^{5} \frac{(5-k)!\,k!}{6!} \left(\sum_{s \subseteq S_k \setminus m : |s|=k} [L(s \cup m) - L(s)] \right). \tag{D.19}$$

D.3.1 Parametrizations without occupational heterogeneity

I need to define the occupationally homogeneous correspondent of each model mechanism for the Shapley–Owen–Shorrocks decomposition. This is straightforward for some parameters: the homogeneous offer arrival rate is a single scalar λ, the homogeneous switching cost is a single scalar c, and the homogeneous job separation rate is a single scalar δ. For the other parameters, I proceed as follows:

- the homogeneous wage schedule is the common transition matrix $\chi = \{\chi_i^w\}_{i,w}$;
- the homogeneous flow utility is the common log wage profile $u_i = \beta \log \mathrm{w}_i$; and
- the homogeneous wage offer distribution is

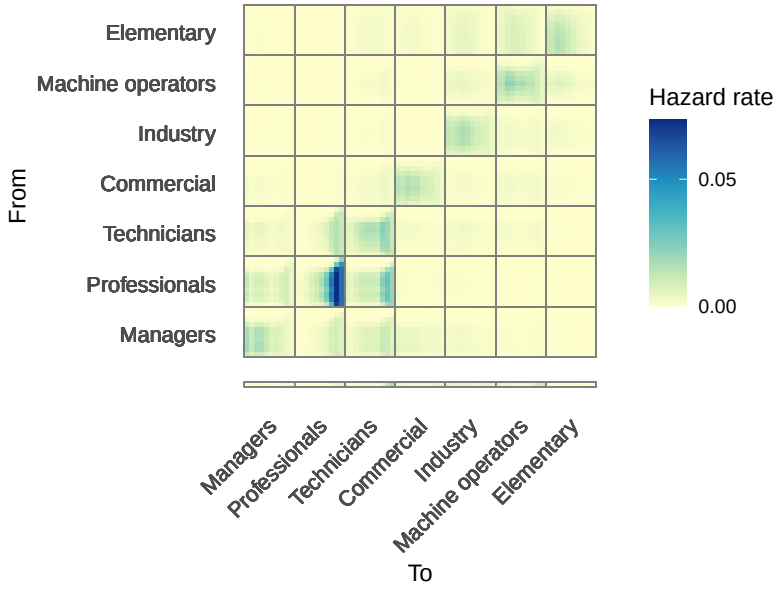
$$f^w = \begin{cases} \Lambda(\phi_w) & \text{for } w = 1 \\ \Lambda(\phi_w) - \Lambda(\phi_{w-1}) & \text{for } 1 < w < W \\ 1 - \Lambda(\phi_{W-1}) & \text{for } w = W \end{cases}. \tag{D.20}$$

E Additional Results

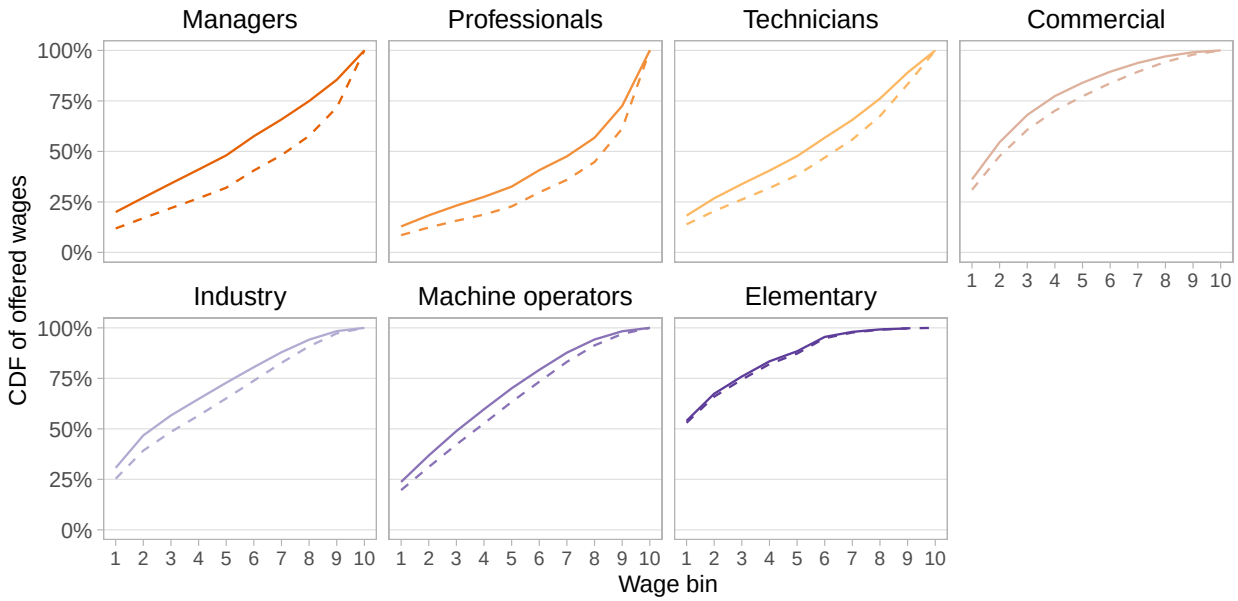
This appendix contains additional results corresponding to the baseline structural model with and without unobserved heterogeneity as well as career simulations. Further results are reported in the Online Appendix. Back to Section 4.

E.1 Baseline model

Appendix Figure E.1: Hazard rates

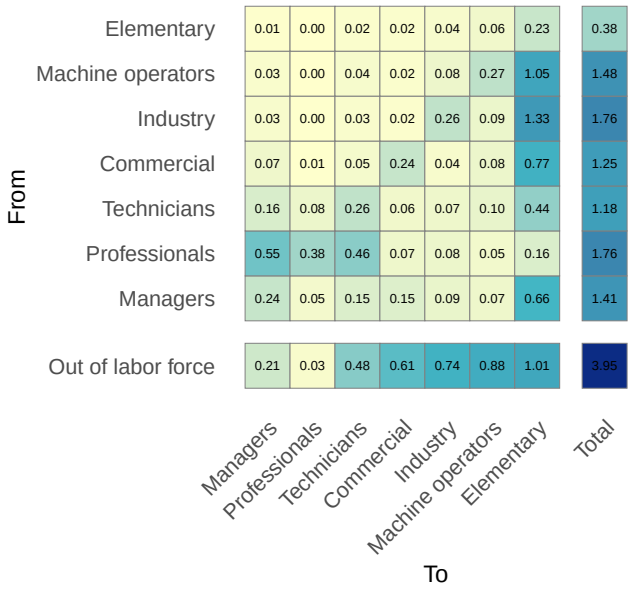


Appendix Figure E.2: Offered vs. accepted wages



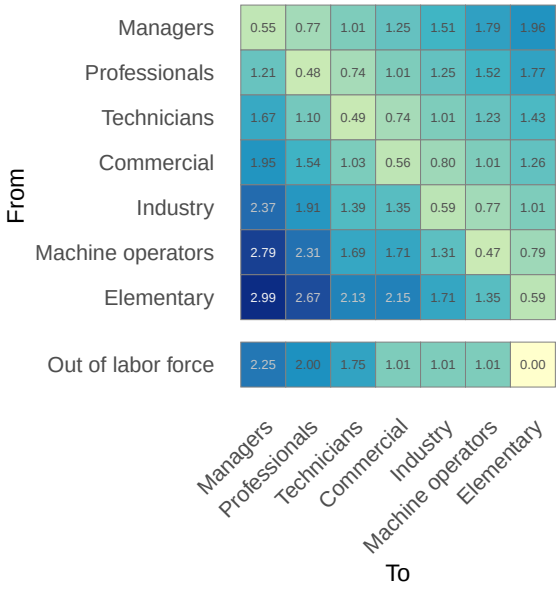
Notes: Solid lines are offered wage CDFs. Dashed lines are accepted wage CDFs. Back to Figure 4.1.

Appendix Figure E.3: Offer arrival rates



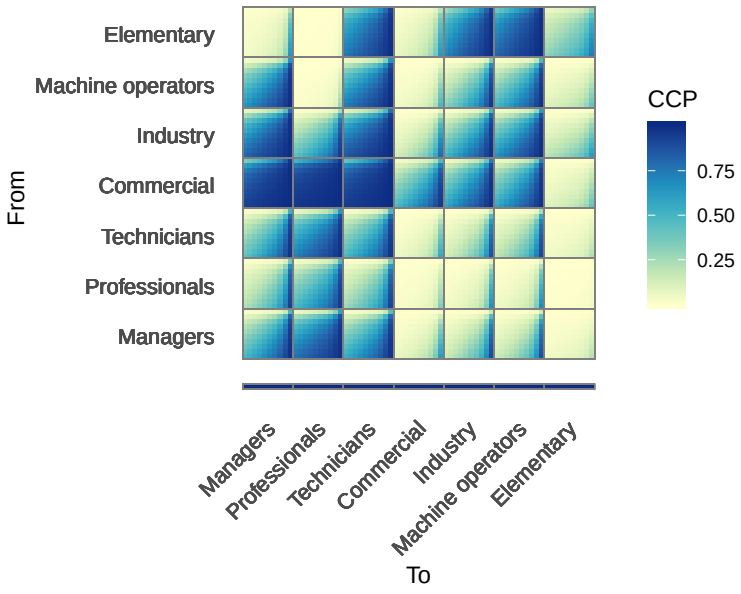
Notes: Back to Table 4.1.

Appendix Figure E.4: Mean switching costs



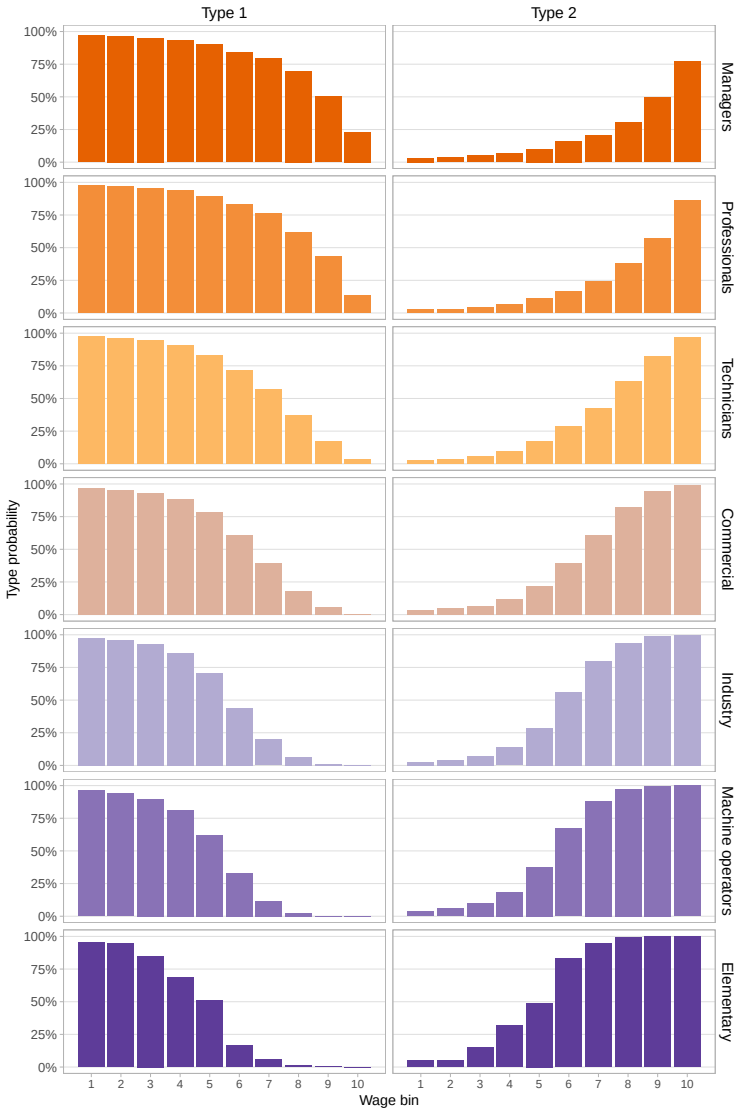
Notes: Back to Table 4.2.

Appendix Figure E.5: Conditional choice probabilities of accepting offers



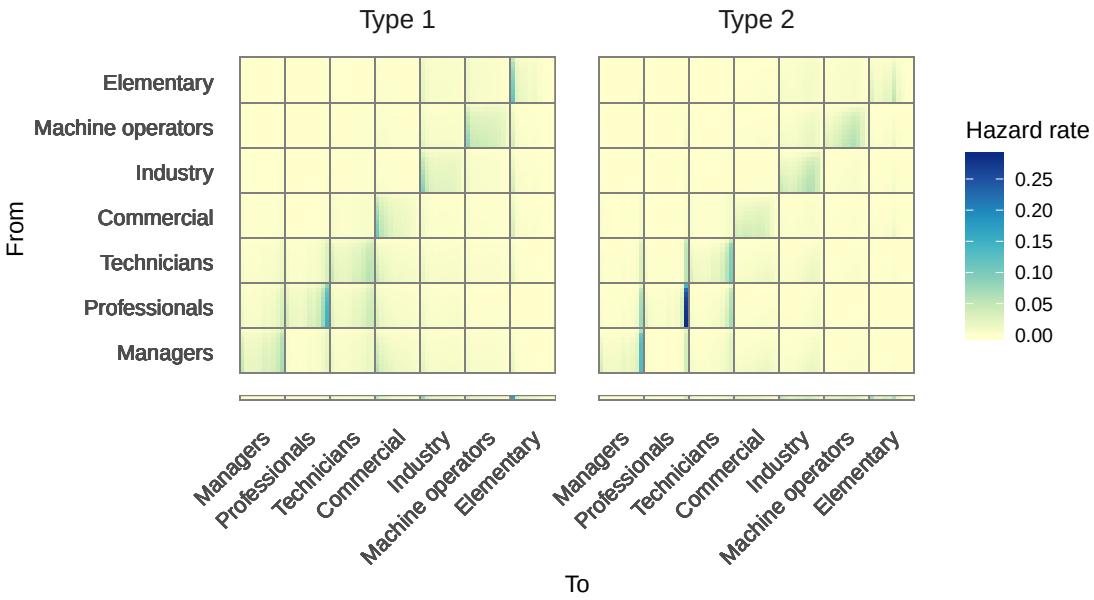
E.2 Baseline model with unobserved heterogeneity: two types

Appendix Figure E.6: Type probabilities

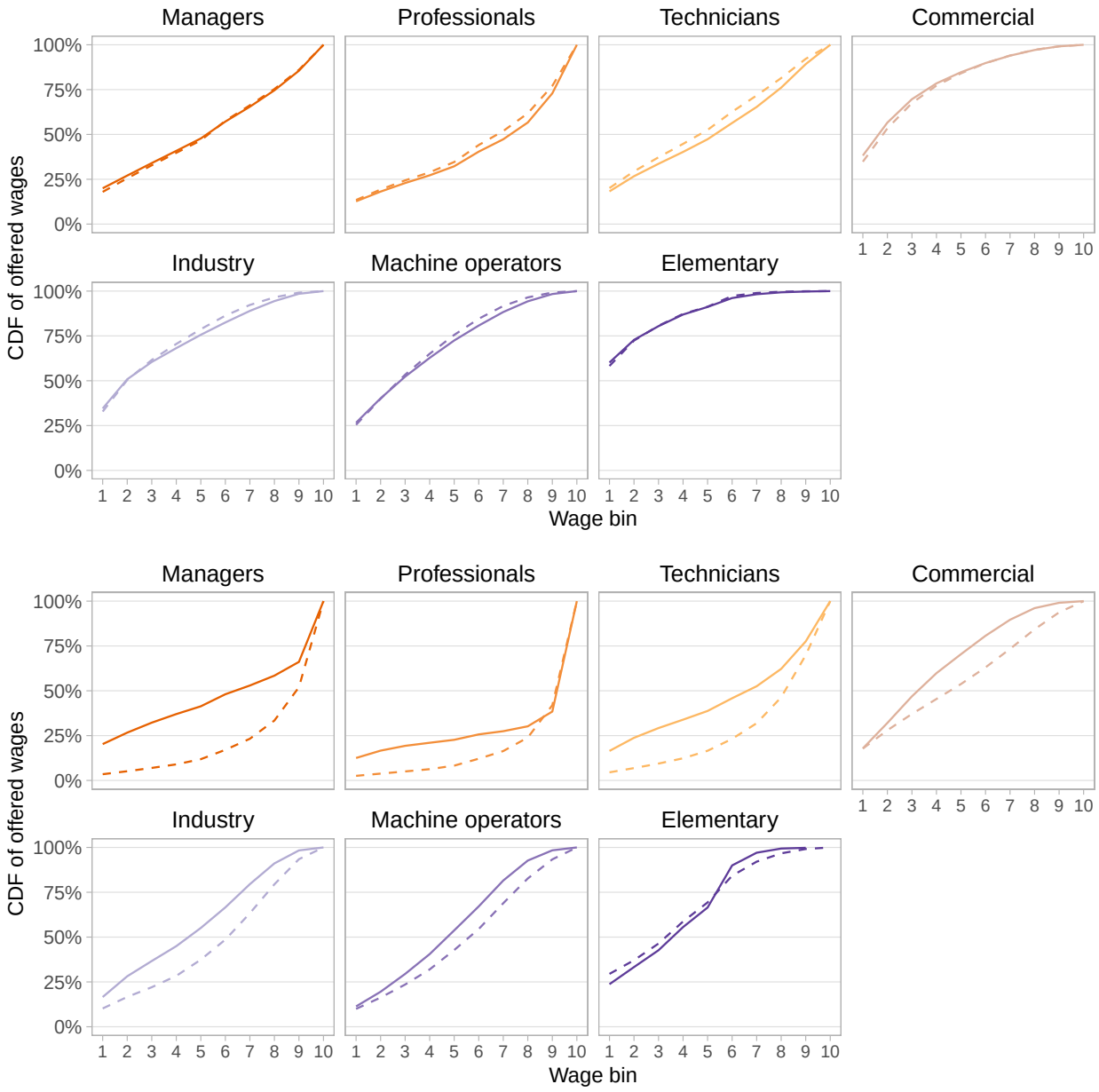


Notes: Back to Figure 4.2.

Appendix Figure E.7: Hazard rates

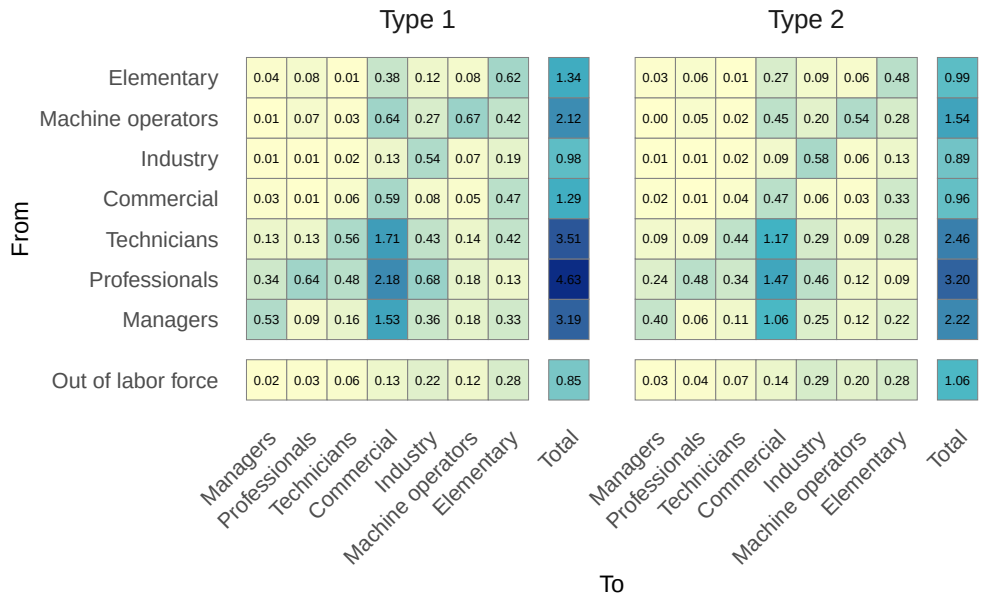


Appendix Figure E.8: Offered vs. accepted wages

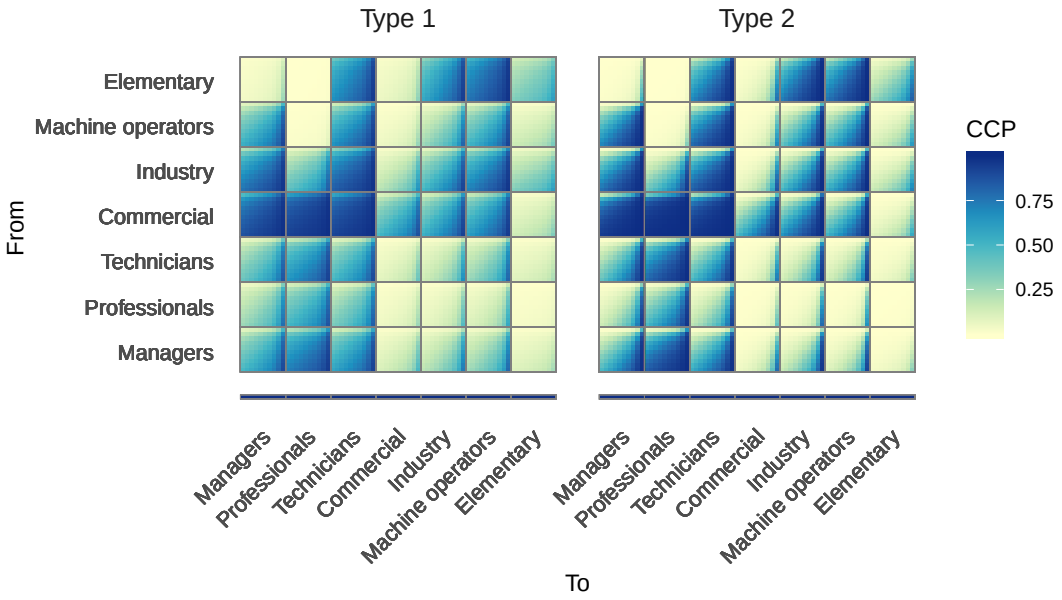


Notes: Solid lines are offered wage CDFs. Dashed lines are accepted wage CDFs. Back to Figure 4.3.

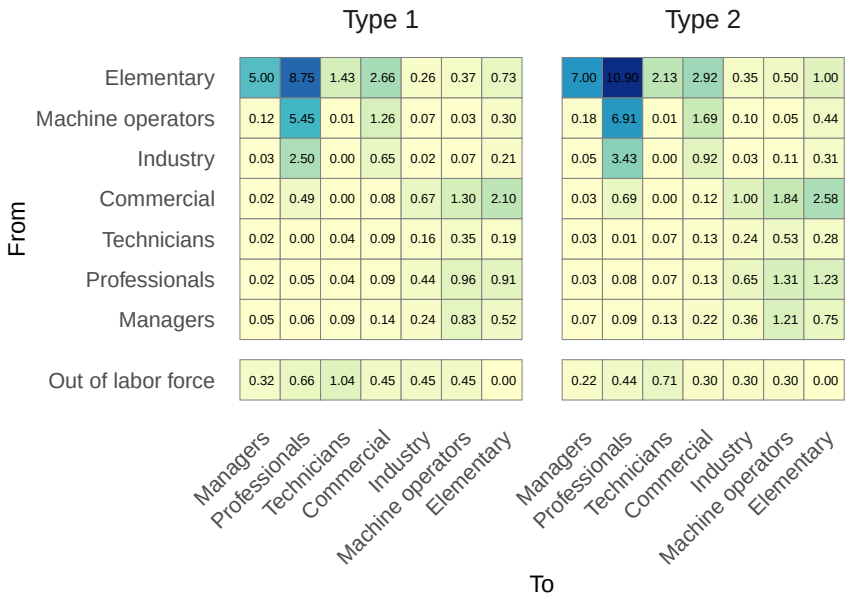
Appendix Figure E.9: Offer arrival rates



Appendix Figure E.10: Conditional choice probabilities of accepting offers



Appendix Figure E.11: Mean switching costs



Notes: Back to Table 4.5.

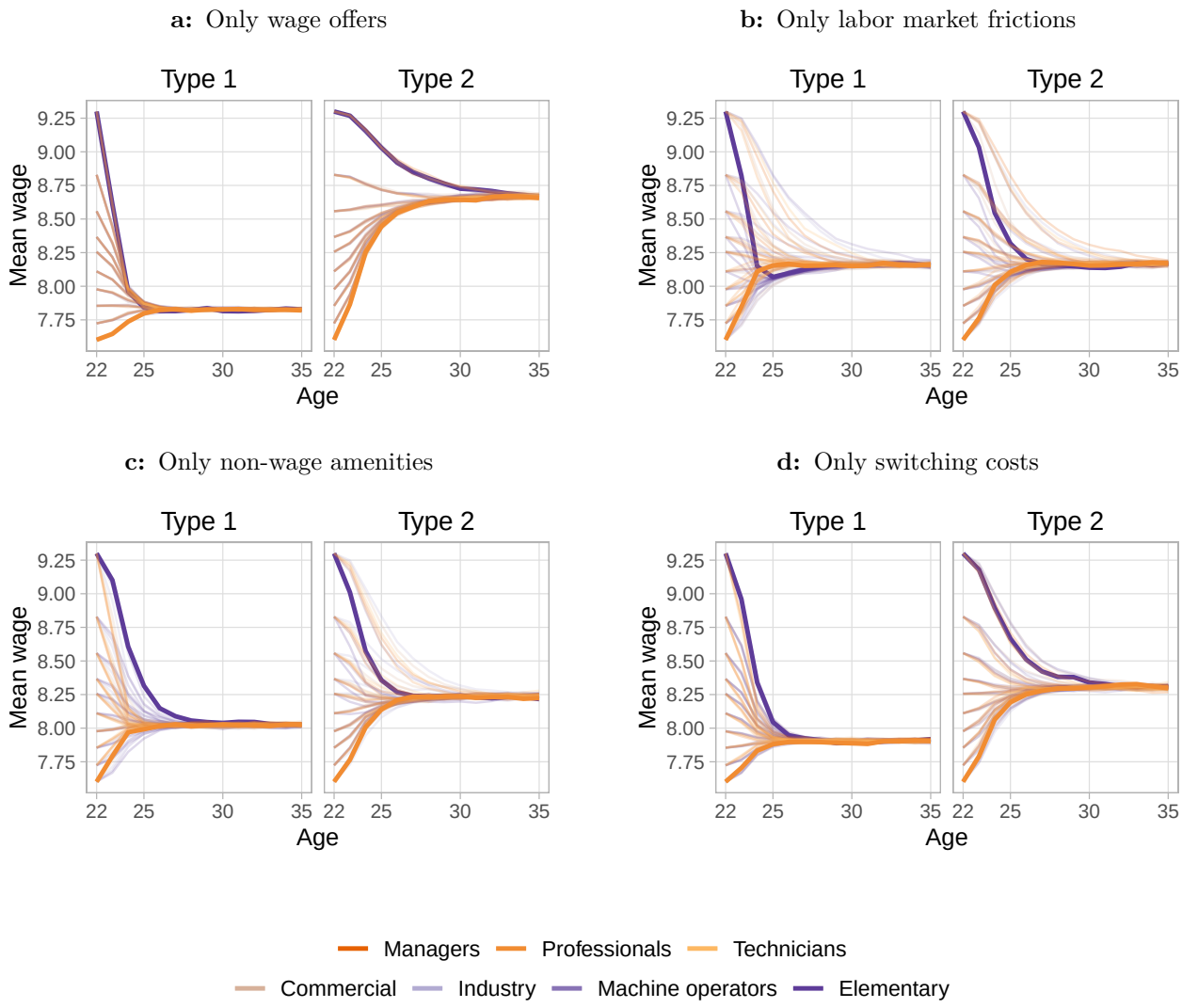
E.3 Career simulations

Appendix Table E.1: Bayesian Information Criteria of counterfactual model estimates

Estimates	**BIC**	
	No unobs. het.	*2 types*
Baseline	13,356,714.90	13,247,044.19
Occupationless benchmark	14,501,118.10	14,453,636.43
Only wage offers	14,333,848.38	13,909,716.75
Only labor market frictions	13,557,265.13	13,556,405.41
Only preferences	14,409,294.71	13,954,330.06
Only switching costs	14,190,990.82	13,569,808.03

Notes: BIC $= -2 \log \hat{L} + k \log N$ where $\hat{L}$ is the likelihood of the model, k denotes the number of parameters and N denotes the sample size. Back to Table 5.1.

Appendix Figure E.12: Ex ante wage profiles by heterogeneity source



Notes: Simulated wage profiles from auxiliary hazard estimates. Mean log wages by age across 2,500 simulations for each initial occupation-wage pair. Thick orange line: ex ante wage profile of a worker starting in a professional job in the lowest wage bin. Thick purple line: ex ante wage profile of a worker starting in an elementary job in the highest wage bin. Back to one-type results in Figure 5.2.