Amenities and Job Mobility over the Life Cycle*

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Abstract

A long established fact is that job mobility contributes greatly to earnings growth of younger workers, yet matters little at later stages in life. In lieu of earnings, this paper shows that changing employer matters greatly for welfare of older workers as they move towards firms with higher general amenities. To this purpose, I estimate firm amenities through a model of worker flows, which uses a revealed-preference argument to infer the value that workers assign to unobserved firm characteristics.

The findings reveal that job-to-job transitions increase firm amenities by 0.22 units of log-earnings or 24.6% in terms of earnings. Compared to young workers below the age of 35, the average firm amenity increase for older workers above the age of 45 is 33% larger, indicating the growing importance of firm amenities over the life cycle.

Accounting for these differences matters for welfare inequality between and within age cohorts. Compared to log-earnings alone, firm amenities double the real welfare difference between young and old workers and they account for all of the increase in welfare inequality within cohorts.

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1 Introduction

Firms differ in the quality of life which they can provide to their employees. While some companies offer great flexibility, others lure workers with enticing benefits or the promise of greater social prestige. As employees spend a large portion of their days at work, these components of firm heterogeneity become an important factor of their welfare. Recent work by Sockin (2021), for example, uses Glassdoor reviews to show that intangible firm characteristics such as work-life balance, management culture and respect towards employees directly influence reported job satisfaction, while Sorkin (2018) estimates that half of the firm premium can be accounted for by compensating differentials for varying levels of firm amenities. To understand the magnitude of labor market inequality, it is important to account for these systematic differences between firm amenities.

"Choose a Job You Love, and You Will Never Have To Work a Day in Your Life", goes a popular proverb about the importance of an enjoyable work life. But do workers move upwards on the amenity-ladder of firms over the course of their careers? If so, do differences in job mobility and firm amenities contribute to welfare inequality between young and old? To answer these questions, I estimate the firm amenity value through revealed preferences of employees which choose to move to a new employer similar to the method developed in Sorkin (2018). I build upon the method by allowing for differences in the compensation between old and new job in the estimation, which lets me convert the estimated firm values into monetary units[1]. As a result, I find that workers climb up the firm-amenity ladder. The change in firm amenities for an average voluntary job-to-job transition contributes to welfare on a scale equivalent to 0.22 units of log-earnings.

Behind average amenity increases through job mobility hides substantial heterogeneity with respect to worker demographics. While job mobility increases amenities for workers at all ages, it matters much more for older workers at later career stages, who increase firm amenities through job-to-job transitions by 33% more compared to their younger peers. The pattern holds even after controlling for the fact that older workers tend to be situated at higher rungs of the earnings distribution. These results are important for our understanding of the evolution of worker compensation over the life-cycle. While it has long been noted that early career changes are import for the wage progression of young workers (Topel and Ward, 1992), my findings suggest that job mobility of older workers remains highly relevant to their welfare. Indeed, accounting for firm amenities roughly doubles the difference in earnings between workers aged 25 and 55. For workers above the age of 40, moreover, earnings growth alone disappears almost entirely. Moving to firms with better amenities thus becomes the main engine of welfare growth for older workers.

Accounting for firm amenities also reveals additional patterns of inequality within cohorts. To this purpose, I measure the variation of welfare that arises from workers being employed by different firms. I find that older workers move up the firm amenity ladder unevenly, which leads to the fact that the variation in firm amenities is 14% higher among workers between ages 45 and 55 compared to younger workers below the age of 35. This is interesting, as variation from earnings alone is roughly constant between age cohorts, which does not point towards rising inequality over the life-cycle.

My findings are also more broadly relevant to our understanding of labor market inequalities due to firm heterogeneity and how workers move up or down the firm ladder. Firm-ladder models are

[1] The same approach has been recently used by Lehmann (2022) to study the evolution of firm compensating differentials over time.

an important building block to explain the implications of job-to-job transitions for labor market heterogeneity, both theoretically (Burdett and Mortensen, 1998) and empirically (Haltiwanger et al., 2015). The relevance of non-pay components in regard to moving up the firm ladder has been emphasized by Jarosch (2021). This paper accounted for differences in separation risk between firms to document that workers not only move to high-paying firms, but also firms with lower separation risk. In contrast, I estimate firm amenities as a residual to explain job transitions, which allows the estimates to capture abstract and hard-to-measure characteristics such as culture and management style. By controlling for differences in the separation risk between firms, I find that differences in job security account for only 15% of the average gains from job-to-job transitions. My findings therefore suggest that further, less tangible components of firm amenities are important.

The rest of the paper is structured as follows. Section 2 introduces the data source and presents stylized facts about job mobility over the life cycle. Section 3 introduces the model and theoretical assumptions. Section 4 summarizes the results while section 5 concludes.

2 Data & Stylized facts

I use data from the Austrian Social Security Database (ASSD, Zweimüller et al. (2011)), which includes labor market records of Austrian workers since 1972. The data covers information on employment status as well as yearly earnings for workers in private sector employment. Also rudimentary demographic information of individuals including the nationality, age and gender is available. The most important feature, however, is the fact that individual labor market careers can be followed over a long horizon through anonymized personal identifiers, which makes the data ideally suited to study the evolution of labor market characteristics over the life-cycle.

Firms can be identified through unique firm identifiers, although significant caution has to be applied, since identification numbers may be reused after a firm ceases to exist. Moreover, the data does not provide detailed information on firm dynamics and oftentimes disappearing firms are reassigned to different identification numbers for administrative purposes such as renaming. I use the worker-flow approach emphasized by Fink et al. (2010) to identify firm identifiers in the data which belong together. Whenever 90% of the workforce of a firm disappear from one firm identifier and reappear together at a different firm identifier, making up 90% of employment under the new identification number, then I define the two firm identifiers to belong to the same original firm. I allow for a single employee to remain at the exiting firm, since in the data many firm identifiers keep being used with only one employee before disappearing from the records altogether.

The ASSD offers detailed spell level data up to the precise dates from which an individual was registered in a specific labor market state. Since this level of granularity is unnecessary for my research question, I reduce every worker to one observation per month by taking the status reported on a reference day (the 15^{th} of each month). Through this method, I create an unbalanced panel of all workers employed in Austria between 1990 and 2009.

Income is measured as monthly reported earnings at the firm at which the worker was employed on the reference date divided by the number of days that the worker was employed at the firm. Unfortunately, I do not observe hours or part-time work. This restriction is unfortunate, since it requires me to reduce the sample significantly. Since reduced working hours are an important reason for lower earnings for women and older workers, their inclusion would severely bias the estimation of amenities. I therefore restrict the main sample of job movers to men, since part-time work is least prevalent in this demographic during the sample period. For the analysis and stylized facts, I restrict the sample to workers between the age of 21 and 55. The reason for the cutoff at age 55 is that a significant share of workers retire between the age of 55 and 60 over the sample period from 1990 to 2010, introducing selection on income and job mobility among the stayers. Table 1 shows summary statistics of earnings in the data by age groups and gender[2].

Table 1: Aggregate statistics by worker age group

Age	All	20-30	31-40	41-50	51- 64
# of unique workers	5887949	2342977	2386739	2158886	2073389
# of unique workers (men)	2974837	1199323	1216317	1096707	1027619
mean (sd) of daily earnings (all)	67.07 (30.83)	58.88 (23.61)	68.02 (31.21)	70.17 (32.76)	74.12 (34.55)
mean (sd) of daily earnings (men)	78.25 (29)	65.38 (22.98)	80.64 (28.12)	83.89 (29.76)	86.07 (31.55)
mean (sd) of daily earnings (women)	53.75 (27.46)	51.03 (21.91)	52.65 (27.69)	55.77 (29.4)	57.22 (31.41)
average size of employer	923.38	721.44	929.92	1040.96	1052.33

Notes. The sample includes all employed workers in Austria between 1990 and 2009. Daily earnings are in EUR.

The main variable of interest for this paper are direct job-to-job transitions. In an ideal data set, I would observe whether the employee had the new job offer on the table while still being employed at her old firm. Unfortunately, social security data is not ideal in the sense that I observe neither the offers made nor the reason for quitting. As a compromise, I define a job-to-job transition whenever a worker changes employment and has been in unemployment or non-employment for at most one month, which is more stringent than what has been used by many comparable papers[3].

I then define labor market transitions whenever I observe a change in the reported state from one month to the next. Importantly, I observe when a worker transitions into or out of unemployment on a monthly basis. Similarly, I record the different rates at which firms hire from unemployment. This information will become important later, as it will allow me to distinguish between firms which hire aggressively and consequently have many of their offers turned down and firms which are more cautious in their hiring efforts.

In the next section, I present a set of stylized facts on job mobility over the life-cycle which serve as further summary statistics of the data and to motivate key points in my paper. In particular, it will become clear that job-to-job transitions matter for earnings growth but fail to tell the full story.

[2]Similar information firms can be found in table A.1 in the appendix.

[3]Due to the quarterly periodicity of their data, Haltiwanger et al. (2018) and Sorkin (2018) define a job-to-job transition whenever at most one quarter of unemployment has been observed.

2.1 Stylized facts

The first fact concerns the well-known finding that earnings growth is concentrated to the beginning of careers. In figure 1, I show the average daily earnings as a function of age separately for men and women. On average, earnings growth flattens out around age 30, with only modest increases towards the end of working life. This is partly driven by a decrease of women's average earnings between age 30 and 40, yet also the the earnings curve of men flattens visibly after the age of 30.

The slowdown of earnings growth at the age of 30 coincides very well with the concomitant decline in job mobility. Figure 2 shows the job-to-job transition rate for different demographic groups, which is defined as the number of job-to-job movers over the total number of employed workers in a given month and within a specific group. Young workers exhibit the highest job mobility with monthly job-to-job transition rates around 3% for people of age 20. Job mobility quickly drops to around 1.5% monthly transition rates at around 40 years of age. Towards the end of a career, only 1% of employed workers transition to a new company. Other measures of job mobility decline, too. Figure A.4 in the appendix shows the decline in the employment-to-unemployment ("EU") rate at early ages, while figure A.5 shows a fall in the unemployment-to-employment ("UE") rate. Why then should we focus on direct job-to-job transitions as the key variable of concern with respect to declining job mobility?

The reason is that job-to-job transitions contribute strongly to the earnings trajectory of young workers - a finding that has been popularized as early as Topel and Ward (1992) - but not to that of older workers. As a third empirical fact, figure 3 shows the average change in log of daily earnings conditional on a job-to-job transition for workers of different age. At the onset of their working lives, workers receive an average increase in daily earnings of around 10% after changing employer directly, whereas in later career stages this number drops to around 4%.

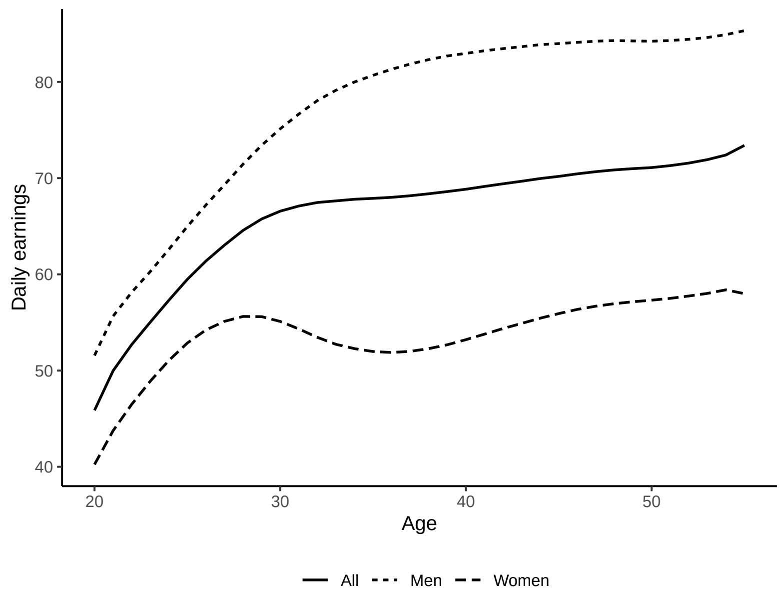
The increase in earnings conditional on changing employers may be biased, however, by the fact that employees are in a position of increased bargaining power when they negotiate a new offer. In this case, job transitions contribute to earnings growth simply via a redistribution of rents between firm and worker. To answer whether workers move to systematically higher paying firms, I decompose earnings into individual worker and firm fixed effects as in Abowd et al. (1999). I aggregate work spells to quarters by averaging daily earnings and keeping only worker-quarter observations where the worker was employed for at least two months at the same firm. Since I do not observe hours, I only include men in the estimation. I first residualize log daily earnings on observables (firm tenure, age, squared terms and a dummy for native workers). I then decompose residualized log earnings $\tilde{y}_{i,t}$ based on the equation

$$\tilde{y}_{i,t} = \alpha_i + \gamma_{J(i,t)} + \epsilon_{i,t} \tag{1}$$

into a worker fixed effect α_i and firm fixed effects γ_j, where $j = J(i,t)$ denotes the firm at which worker i was employed in quarter t. With the estimated firm fixed effects, I calculate the average contribution to earnings growth that can be attributed to a change in the firm and display the results in figure 5. The results mirror the findings of figure 4, as upwards movement on the AKM firm wage matters more for women than men. However, on average every job-to-job transition is associated with a step up o the firm ladder, albeit a small one.

The evidence presented so far suggests that job mobility does not add much for older workers in terms of monetary benefits and should therefore be only of second order concern. On the contrary, I argue that the focus on average earnings growth distracts from the fact that older workers systematically

Figure 1: Average daily earnings by age and gender



move to firms that provide higher amenities. The motivating fact to consider is that the apparent drop in the average wage increase that workers receive after changing firms hides the fact that the distribution of wage changes is spread out widely. As can be seen in figure 6, the distribution of log wage changes conditional on a transition for men is shifting left as workers age. A large share of workers - 43 % across all age groups - accept cut in earnings to move to a new job. To some extent, these events may relate to idiosyncratic shocks in preferences (family, health, ...). On the other hand, there are systematic differences between jobs and firms along many dimensions, which further factor into an employment decision. Job quality is vastly different between different industries, and some occupations and firms may simply be more prestigious than others.

Overall, the large share of workers which accept an earnings cut indicate that some factor besides changes in earnings determine the choice of employment for many workers. In the next section, I will show how the revealed preferences of job-to-job movers can be used to derive and measure of how firms differ with respect to the *systematic* part of non-pay compensation.

3 Estimating a revealed-preference ranking of firms

The descriptive evidence on job mobility from the previous section gives rise to a puzzle. Why do workers move in flocks to lower paying firms? Can their behavior be explained by an economic force? To answer this question, I estimate a reduced-form model of job-to-job transitions in which firms differ with respect to the amenities which they offer to their employees. These amenity differences generate variation in the utility offered by firms which is not directly linked to pay. Workers may systematically accept lower pay at a new job if they are sufficiently compensated through amenities.

Figure 2: Monthly job-to-job transition rates by age and gender

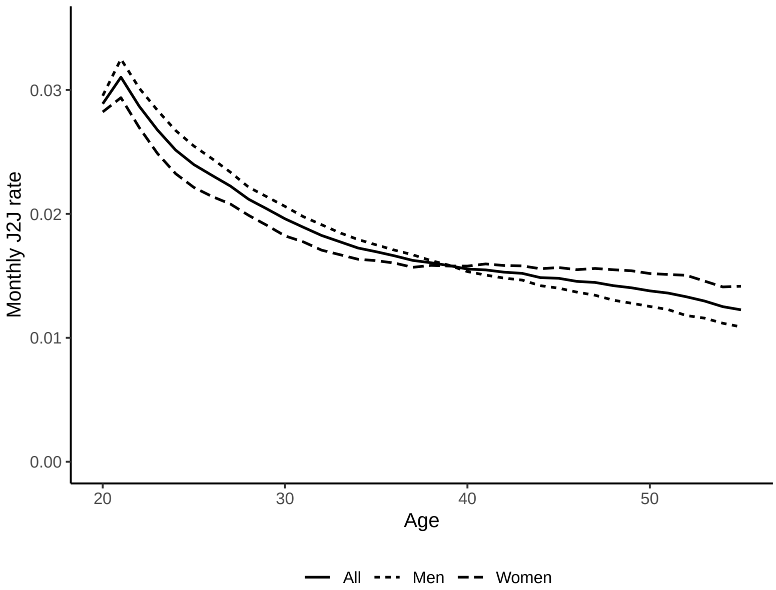


Figure 3: Average change in Log income conditional on a job-to-job transition

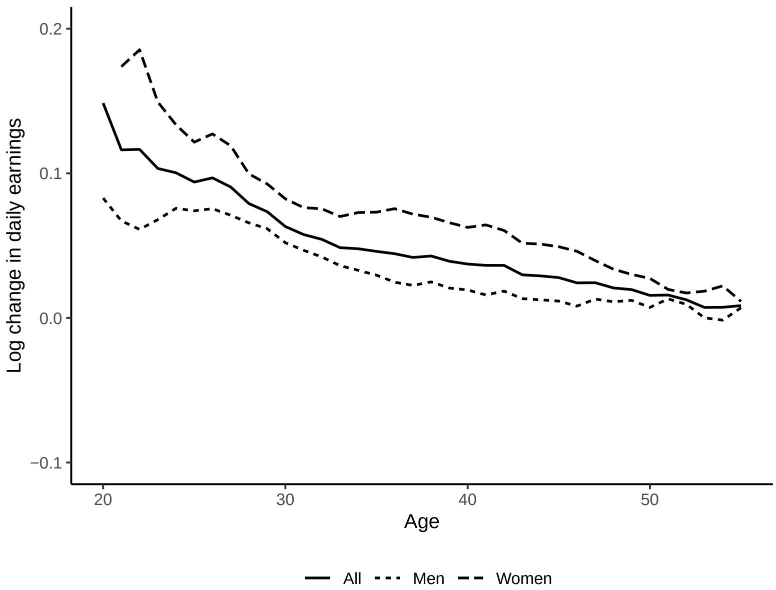


Figure 4: Firm fixed effect in log(wages) from an AKM decomposition

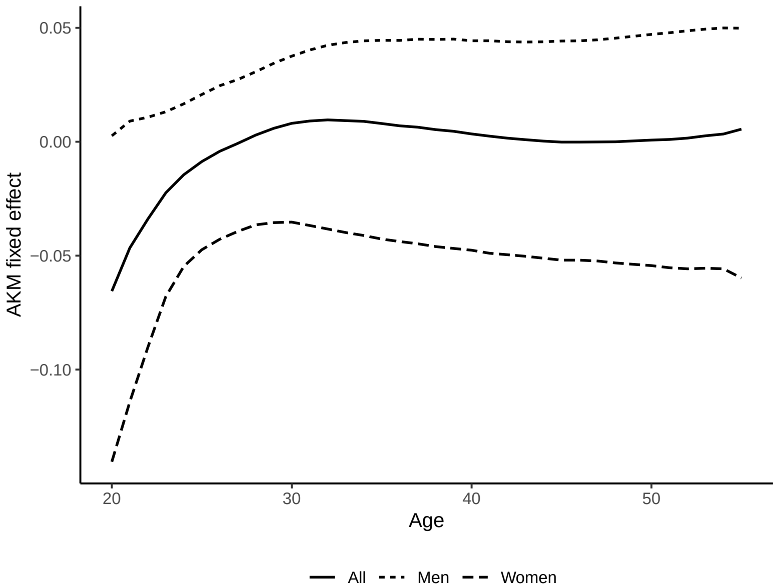


Figure 5: Average change in income change AKM firm fixed effect condition on a job to job transition

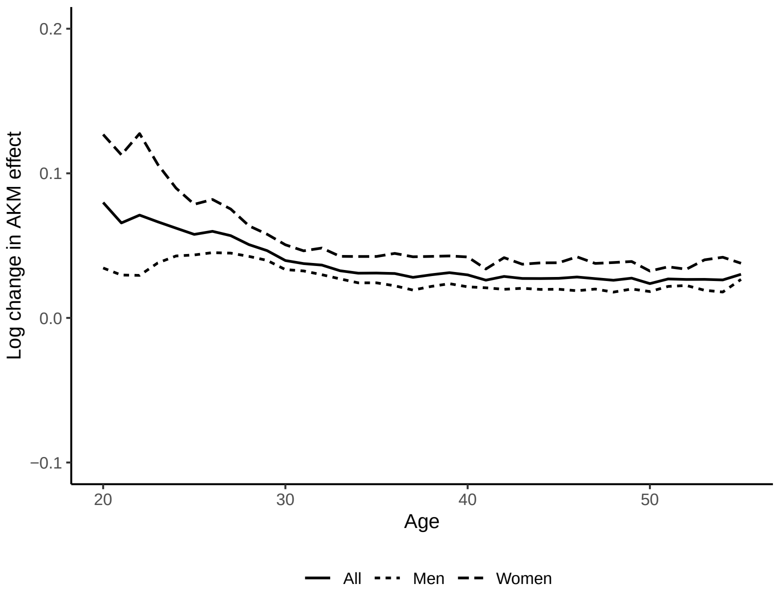
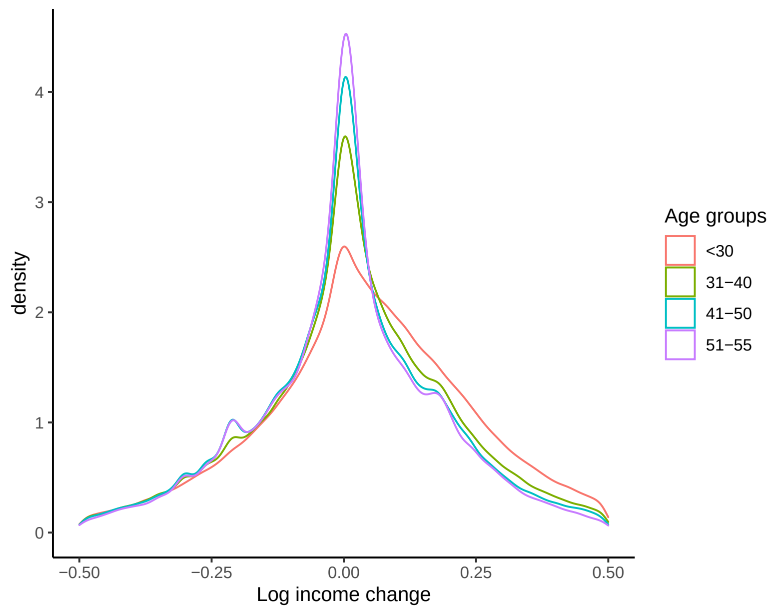


Figure 6: Density of Log income change condition on a job to job transition (men)



To estimate the systematic differences in utility offered by firms, I make use of a model of revealed preferences on the labor market which was pioneered by Sorkin (2018). The idea of the model is simple. If firms differ with respect to the amenities which they offer new hires, then a job-to-job transition can be interpreted as a revealed preference between the origin and destination firm. The pattern of job-to-job transitions becomes informative of the preference ranking which workers have over different firms.

As an illustrative example, suppose that we observe only two flows between three firms - A, B and C. One worker changed employment from firm C to firm B, another worker moved from B to A. By revealed preferences of workers, the ranking of firms is $A \succ B \succ C$. In a real setting, however, the likely existence of cycles violates transitivity and prevents the formation of a simple preference-ranking as in the example above. Instead, I use a ranking that relies on the expected number of flows between firms or, equivalently, on the probability that a worker at firm B accepts a job from firm A. If the probability is high, we would infer that firm A ranks highly relative to firm B. Overall, we would expect more direct job-to-job transitions from lower-ranked to higher-ranked firms. Moreover, higher-ranked firms should experience less job-to-job transitions to lower-ranked firms. Intuitively, poaching employees should become easier the higher the difference in ranking.

In essence, the ranking can be formulated as a discrete choice problem. Suppose that firms offer a fixed utility level γ to all workers. Differences in γ between firms could be due to any non-observable factor that is constant across all workers (e.g. work-life balance, pressure, social appreciation, . . .). Apart from this component, workers receive utility through specific observable factors summarized in x. Most importantly, x will consist of pay but it could also include any other variable which is deemed to be important for labor market decisions.

The utility which worker i derives from working at firm A then is

$$u_{i,A} = \gamma_A + x'_{i,A}\beta + \eta_{iA}, \tag{2}$$

where η is an i.i.d. Gumbel-distributed random variable and describes idiosyncratic taste shocks of individual workers that are orthogonal to the common amenity value γ_A and observables $x_{i,A}$.

Suppose now that worker i is presented with a new job offer by firm B. The offer is accepted whenever $u_{i,B} > u_{i,B}$. Since the idiosyncratic taste shocks at each firm are independent draws from a Gumbel-distribution, the difference $\eta_{i,B} - \eta_{i,A}$ follows a Logistic distribution and therefore the probability of accepting an offer at firm B for a worker at firm A takes the functional form

$$Pr(u_{i,B} > u_{i,A}|\Gamma, X) \;=\; \frac{1}{1 + exp\left(-\gamma_B + \gamma_A - (x'_{i,B} - x'_{i,A})\beta\right)} \tag{3}$$

At heart, the model is strongly related to PageRank (Page et al., 1998), the method by which Google initially ranked websites in its search results. For PageRank, links from one website to another are interpreted as a measure of relevance of the target site. More important sites are referred to by *other important sites*, while references from unimportant sites should be discounted[4]. The same intuition applies in the context of job-to-job transitions, as poaching employees from other highly ranked firms is a stronger signal of the high rank of the destination firm than a transition from a lower ranked firm. This highlights the difference between a pure measure of centrality - for example through counting the number of poached workers at each firm - and the model proposed here. In the present context, the ranking of a firm relies iterativly on the ranking of all destination and origin firms with which it had a direct exchange of employees.

To better understand under what conditions the underlying value ranking of firms is identified from job-to-job transitions in the data, it is helpful to consider the determinants of flows between firms. Consider firms A and B with a recorded job-to-job move of a worker i from firm A to firm B. The likelihood of observing the move is determined by two factors: the probability with which firm B makes offers to workers at firm A and the probability that the job at firm B dominates in value. Only the second component is revealing about the revealed-preference ranking of firms, while the first part is related to the hiring effort of the destination firm. Since the data only contains job offers that were accepted by a worker, I cannot distinguish between a firm that is attractive and a firm that makes many offers.

As an example, consider two sets of offers between firms A and B from table 2. The observed job-to-job transitions are equivalent in both examples: three workers each accepted an offer to move from firm A to firm B and from firm B to firm A, respectively. In table 2a on the left, both firms made a total of five offers, of which two were rejected. A ranking based on the simple choice probabilities would conclude that both firms are of equal rank. In table 2b on the right, however, firm A's offer was rejected by workers twice as often as offers by firm B. To poach three workers, firm B had to expand less offers. A ranking based on choice probabilities from the observed accepted offers, however, would still rank firm A and B equally, even though it is more likely that firm B is ranked higher - and thus its offers are rejected less frequently. A second explanation for the difference in rejected offers between firms A

[4]PageRank can be interpreted through a "Random Surfer Model": a hypothetical user starts at a random website and clicks on one of the available links with equal probability to jump to the next website. Here, the user repeats the procedure and selects the next website from the available links at random, ad infinitum. PageRank then returns the stationary probability distribution for the visits on each website.

Table 2: Two observationally equivalent data sets with different implications for the ranking between firms A and B. In both examples, only accepted offers are observed but firms differ in the total number of offers that they issue.

$A \rightarrow B$	$B \rightarrow A$
accept	**accept**
accept	**accept**
accept	**accept**
reject	reject
reject	reject

(a) $A \sim B$: Both firms successfully poached three workers and were rejected twice.

$A \rightarrow B$	$B \rightarrow A$
accept	**accept**
accept	**accept**
accept	**accept**
reject	reject
reject	reject
reject	
reject	

(b) $B \succ A$: Both firms successfully poached three workers. But A was rejected four times while B was rejected only twice.

and B could stem from the fact that firms may be different in size. A large firm will have more workers poached by competitors, while the number of offers that its current workers rejected is missing in the data.

To correct for these issues and allow for heterogeneity in the hiring intensity across firms, I make the following simplifying assumptions about the hiring process.

Assumption 1 (Offers)**.** *Assume that workers at each firm receive a job offer at rate λ. The offer is drawn from the distribution of all firms in the economy proportional to the hiring intensity f of each firm.*

Assumption 1 allows firms to differ in the rate at which they issue offers to prospective workers at other firms in the economy. The probability for an offer to a worker at firm A by firm B is then proportional to the size N_A of firm A and the hiring intensity f_B at firm B. In expectation, the observed moves $M_{A,B}$ from firm A to firm B in a given interval of time are jointly determined by the share of workers at A who receive an offer to work at B and the share of offers accepted.

$$\mathbb{E}[M_{A,B}|\Gamma, X] = \underbrace{N_A \; \lambda \; f_B}_{\text{Offers made}} * \underbrace{Pr(u_B > u_A|\Gamma, X)}_{\text{Offers accepted}}$$

Equivalently, the expected number of unobserved rejections $R_{B,A}$ of offers that firm A issues to firm B take the form

$$\mathbb{E}[R_{B,A}|\Gamma, X] = \underbrace{N_B \; \lambda \; f_A}_{\text{Offers made}} * \underbrace{Pr(u_A \leq u_B|\Gamma, X)}_{\text{Offers rejected}}$$

Since the probability of rejecting an offer from firm A when at firm B is symmetric to the probability of accepting an offer from firm B when at firm A, the flows of workers are informative about both accepted and rejected offers. In other words, I can use the fact that $\mathbb{E}[M_{A,B}|\Gamma, X] = \frac{N_A f_B}{N_B f_A} \mathbb{E}[R_{B,A}|\Gamma, X]$ to appropriately weight each observed move to control for missing observations due to rejected offers. To derive the appropriate weights, I consider the likelihood function of the exemplary data in table 2, including both accepted and rejected offers between two firms A and B. Denote the set of offers from firm A to firm B by $\mathcal{O}_{AB}$, the observed moves from firm A to firm B by $\mathcal{M}_{AB}$ and vice versa in the opposite direction.

$$
\begin{aligned}
\mathcal{L}(\Gamma|\mathcal{O}, f, X) \propto\ & \prod_{\mathcal{O}_{AB}} Pr\left(u_{i,B} > u_{i,A}|\Gamma, X\right)^{\text{Offer accepted}} \times Pr\left(u_{i,B} \leq u_{i,A}|\Gamma, X\right)^{\text{Offer rejected}} \times \\
& \prod_{\mathcal{O}_{BA}} Pr\left(u_{i,A} > u_{i,B}|\Gamma, X\right)^{\text{Offer accepted}} \times Pr\left(u_{i,A} \leq u_{i,B}|\Gamma, X\right)^{\text{Offer rejected}} \\
\approx\ & Pr\left(u_{i,B} > u_{i,A}|\Gamma, X\right)^{\mathbb{E}[M_{A,B}|\Gamma,X]} \times Pr\left(u_{i,B} \leq u_{i,A}|\Gamma, X\right)^{\mathbb{E}[R_{A,B}|\Gamma,X]} \times \\
& Pr\left(u_{i,A} > u_{i,B}|\Gamma, X\right)^{\mathbb{E}[M_{B,A}|\Gamma,X]} \times Pr\left(u_{i,A} \leq u_{i,B}|\Gamma, X\right)^{\mathbb{E}[R_{B,A}|\Gamma,X]} \\
=\ & Pr\left(u_{i,B} > u_{i,A}|\Gamma, X\right)^{\mathbb{E}[M_{A,B}|\Gamma,X]\left(1+\frac{N_B f_A}{N_A f_B}\right)} \times Pr\left(u_{i,A} > u_{i,B}|\Gamma, X\right)^{\mathbb{E}[M_{B,A}|\Gamma,X]\left(1+\frac{N_A f_B}{N_B f_A}\right)} \\
=\ & \prod_{i \in \mathcal{M}_{AB}} Pr\left(u_{i,B} > u_{i,A}|\Gamma, X\right)^{1+\frac{N_B f_A}{N_A f_B}} \times \prod_{i \in \mathcal{M}_{BA}} Pr\left(u_{i,A} > u_{i,B}|\Gamma, X\right)^{1+\frac{N_A f_B}{N_B f_A}}
\end{aligned}
$$

In the second line, I approximate the likelihood of an unknown number of offers through the expected number of offers - accepted or rejected. Missing rejections are a problem for the identification of the parameters Γ since the likelihood of observing a missing rejection is higher for lower ranked firms. In the third equality, I make use of the relationship between expected accepted and rejected offers between firms A and B derived from the assumptions about job offers above and show that the likelihood contribution of all offers between firms A and B is contained in the observed moves $\mathcal{M}_{AB}$ and $\mathcal{M}_{BA}$ between the two firms, weighted by factor $1 + \frac{N_B f_A}{N_A f_B}$ and $1 + \frac{N_A f_B}{N_B f_A}$.

The intuition for the weighting factors is the following. Consider moves from A to B. Each move is first and foremost informative about the parameters concerning firm B, as it constitutes an accepted offer and thus a revealed preference in that direction. At the same time, the decision of accepting an offer from firm B over firm A is also informative about rejected offers that firm A made in the opposite direction. Since the the choice model is symmetric - choosing B over A is the same irrespective of who made the offer - the only important missing component is the expected number of such rejected offers that A made. Under the assumptions above where each firm is characterized by a hiring intensity f that it directs equally towards all workers in the economy, the ratio of offers between two firms is $\frac{N_B f_A}{N_A f_B}$. We expect to see more offers from A to B if B is relatively larger or if A expands relatively more resources on hiring.

The weights proposed above capture the necessary assumptions to deal with the bias introduced by missing rejected offers, but are not yet sufficient to capture the correct likelihood contribution towards the parameters Γ. The reason is that large firms are more likely to have offers made at their employees, while firms with a large hiring intensity are more likely to issue offers towards employees at other firms. Note from the formulation of expected flows between firms that the expected number of offers made between firms A and B is $\mathbb{E}[M_{A,B} + R_{A,B} + M_{B,A} + R_{B,A}|\Gamma, X] N_A f_B + N_B f_A$ To correct for the imbalances in the number of offers made by different firms, I weigh the offers made accordingly to the the inverse rate $\frac{1}{N_A f_B + N_B f_A}$ at which they appear in the sample. The weights for individual movers from A to B therefore simply to $\frac{1}{N_A f_B}$. After controlling for the absolute intensity with which offers are made between two firms, only the relative intensity of the offering firm matters for the adjustment of the likelihood contribution of an individual move.[5] This leads to the following offer-adjusted log-likelihood contribution of all movers given the set of movers $\mathcal{M} = \{(i, A, B, x_{i,A}, x_{i,B})|i \text{ moves from } A \text{ to } B\}$ given

[5]The approach is closely related to Weighted Exogenous Sampling Maxmimum Likelihood Estimator (WESML) for choice-based sampling protocols proposed by Manski and Lerman (1977).

firm sizes N and offer intensities f.

$$\mathcal{L}(\Gamma|\mathcal{M}, f, X) = \sum_{A} \sum_{B \neq A} \sum_{m \in \mathcal{M}_{AB}} \frac{1}{N_A f_B} \log \left(Pr\left(u_{i,A} > u_{i,B} | \Gamma, X\right)\right) \tag{4}$$

3.1 Offer distribution and exogenous separations

The likelihood from equation 4 indicates that there is a convenient way of estimating the ranking of firms from the sample of accepted job offers by appropriately weighting the observations to reflect different frequencies with which firms appear in the data. Of the two factors, the size of firms is readily available in the data. The number of workers of the origin firm of a job mover in the month before the move constitutes the firm size N_A in the weighting above.

To further inform the hiring intensity of different firms, I make use of a simplifying assumption about the hiring process and decisions of unemployed workers.

Assumption 2 (Hiring from unemployment)**.** *Firms make offers to unemployed workers at the same relative hiring intensity f as towards employees from other firms. Moreover, unemployed workers accept every offer which they receive.*

Assumption 2 allows to use the observed hires of firms from non-employment as an estimate of the hiring intensity, such that $f_A = \mathbb{E}[M_{0,A}]$ where $M_{0,A}$ are observed flows from non-employment towards firm A. The assumption that unemployed workers accept every offer is a helpful simplification, since it implies that the expected flows from non-employment are independent of the ranking of firms such that $\mathbb{E}[M_{0,A}|\Gamma, X] = \mathbb{E}[M_{0,A}]$. [6]

Apart from missing information on the hiring intensity of firms, another limitation to consider is the fact that in a discrete choice framework, preferences over firms can only be inferred if both options are truly in the choice set. In the context of a model of job-to-job transitions, this condition is satisfied in whenever the employee has the option to reject the offer and stay at the current firm. As a first remedy I restrict attention only to job-to-job transitions with at most one month of non-employment between working spells[7] A threat arises from the fact that firms which are subject to a business cycle shock may let their workers know earlier that they are being let go, and therefore incentivize preemptive job-to-job transitions of their employees. As a remedy, I restrict the sample and exclude any transitions which involved rapidly shrinking firms. More precisely, I exclude transitions where the origin firm shrank by more than 5% in the three months preceding the transition. Together with the restriction that workers may be unemployed for at most one month, I argue that these restrictions are enough to exclude any severe bias from exogenous separations.

[6] Another interpretation of the assumption is that non-employment constitutes the worst possible job in the economy, which is obviously a stark simplification of reality. As a reference, Sorkin (2018) has estimated a simple model under assumption 2 and a richer model, in which the probability of accepting an offer for the unemployed depends on the value of job offers. The full model with an endogenized value of non-employment relies on an outer loop which reevaluates the hiring intensity f given a ranking of firms Γ at each iteration until convergence, which is feasible to compute since the ranking in their paper is calculated from a set of just-identified moment conditions. In my setting, it becomes computationally challenging to implement the same approach, since it would require a repeated estimation of maximum likelihood estimators for the ranking. As an advantage over the model in Sorkin (2018) and similar to the idea in Lehmann (2022), however, using Maximum Likelihood allows to directly use observed wages in the estimation step and obtain a unit of conversion between utility and Euros in the model.

[7] Relative to the literature on job-to-job transitions, this is conservative. Papers which rely on US data often have to use quarterly definitions (Hyatt et al., 2014; Sorkin, 2018; Haltiwanger et al., 2018). With a longer time in non-employment, the probability of a voluntary decision by the worker declines. On the other hand, workers may take some time off between jobs for personal reasons and therefore a short period of time would lose too many voluntary transitions.

A final step before the model can be taken to the data concerns the identification of individual firm parameters from the model. Recall from 3 that the contribution of a single job mover from firm A to firm B can be written as a linear combination of Γ, changes in observables ΔX and β), after applying the logistic function. To be precise, the likelihood of an observation i can be written as

$$\ell(i) = \log\left(\text{logistic}\left(T_i \Gamma + \Delta X_i \beta\right)\right)$$

where $T_i = (0, \ldots, 0, \underset{B}{1}, 0, \ldots, 0, \underset{A}{-1}, 0, \ldots)$ is an indicator for transition i with 1 for firm B and a -1 for firm A. Each firm value γ enters the likelihood function of movers with a positive sign whenever a worker joins and a negative sign when a worker leaves the firm. In order for γ to be uniquely pinned down by the individual moves, there has to be at least one inflow into each firm as well as one outflow. In other words, the firm values are only identified on the **set of strongly connected firms**. This differentiates the identification requirements from models of firm value based on earnings à la Abowd et al. (1999)[8], where it is sufficient that firms are connected in one direction of flows.

In the end, the stacked indicator vectors T form the matrix which describes the entire graph structure of the economy. T can be a computationally large object with a lot of sparsity, since many pairs of firms see no transitions between each other. In order to estimate the model, I make use of Python's *scikit-learn*-package (Pedregosa et al., 2011) and its ability to directly handle sparse model objects in estimation.

3.2 Covariates and sample

A key advantage of formulating and estimating a revealed-preference model of amenities through maximum-likelihood is that I can include and control for a variety of coefficients that may affect the choice of a worker between firms. Most importantly, I can include the observed income of workers before and after a job-to-job transition and therefore directly separate pay and amenities in the estimation. This fact has also been noted and used by Lehmann (2022) and constitutes a main methodological improvement compared to Sorkin (2018). To combat measurement error, I use the average worker income in the three months prior and after the transition and control for the log of income changes between jobs.

In principle, the approach allows to control for any number of characteristics which vary from firm to firm. On the one hand, this can be used to directly estimate the contribution to the revealed preference of the worker, and thus the implied value of a characteristic[9]. On the other hand, it helps to further control for confounding variables. Since amenities are estimated as a residual in my model, including further covariates can help to achieve more reasonable estimates of amenities. In order to control for the implicit value of job security, I control for changes in the separation risk as defined by the average annual number of employment-to-unemployment transitions per employee that a firm exhibits over the sample period. Doing so allows me to capture how much of the estimated firm value can be explained by job security, which was recently highlighted as an important determinant for career decisions of workers (Jarosch, 2015).

Table 3 provides summary statistics for the sample of job-to-job transitions. The first column contains the full sample of job-to-job transitions as defined by employer-to-employer transitions with at most one month of inactivity between spells. It further restricts to transitions where the employee had at least

[8] For details, see the discussion in Abowd et al. (2002).

[9] As firms are anonymous in my dataset, I cannot use this approach to explore any further dimensions of amenities.

Table 3: Summary statistics of sample of job-to-job transitions

	All	Restricted	Restricted + connected
# of observations	960398	475609	288727
# of firms	34445	28364	6978
# of workers	671878	372609	234079
Mean age	33.815	33.147	33.118
Mean firm size	558.984	682.893	923.196
Mean Δ separation risk	-0.067	-0.032	-0.046
SD Δ separation risk	-0.03	0.008	-0.011
Mean Δ log(income)	0.052	0.042	0.039
SD Δ log(income)	0.218	0.218	0.21
Share with wage increase	0.612	0.597	0.597

Notes. Column extit"All" includes all job-to-job transitions, defined as employer changes with at most one month of inactivity between spells and at least 6 months of employment at each the origin and the destination firm. For column *"Restricted"*, the sample is further restricted to firms with at least 20 employees at the time of transition, which shrank by at most 5% in the previous quarter and which have hired from unemployment in the previous year. Moreover, earnings changes are winsorized at the 1^{st} and 99^{th} percentile to eliminate bias from measurement error. Column *"Restricted + Connected"* further imposes that firms experience at least 10 job-to-job inflows and outflows and belong to the strongly connected set.

three months of tenure at the previous firm and will work for at least three months at the destination firm.

The second column further restricts the sample to reflect the shortcomings of the estimation method as described above. Specifically, firms may shrink by at most 5% in the quarter before the transition and must have hired from unemployment once in the previous year in order to identify their rank in the offer distribution. Moreover, I restrict the data to firms with at least 20 employees in order to eliminate noise from too many small enterprises. Since measurement error of earnings is a problem, I delete outliers by winsorizing earnings changes at the 1^{st} and 99^{th} percentile.

The last column represents the final sample which I use to estimate amenities. Here, I further restrict the sample to the set of strongly connected firms, i.e. the set of firms which are connected by at least one transition into and out of the connected set. While this is technically sufficient to identify the full set of firm effects, I further strengthen it by requiring at least ten transitions into and out of each firm. On average, job changes in the final sample result in a modest increase in earnings by 3.9%.

4 Results

4.1 Parameter estimates and aggregate results

In the following section, I present estimation results of a model of amenities as introduced above. The choice structure of the model introduced in section 3 allows two different interpretations of the estimated coefficients. On the one hand, the model can be interpreted in terms of the effect that observable covariates and estimated amenities have on choice probabilities between two firms. On the other hand, I can use the fact that I observe changes in income between job transitions and estimate its effect on job transitions. The estimate on income changes allows me to scale the estimated amenity effects into monetary units and use the scaled estimates to interpret the model in terms of the average amenity increase by job transition.

Table 4 shows the parameter estimates for the coefficients on covariates of the choice model as well as aggregate statistics for the estimated firm effects Γ. Through the lens of the logistic discrete choice model, the estimates can be directly interpreted as partial effects on the odds ratio $\frac{Pr(accept)}{1-Pr(accept)}$ between accepting and rejecting a hypothetical job offer. If the difference in earnings at the origin and target firm increases by 1%, the odds of accepting the offer increase by around 2.48%. On the other hand, the odds of transitioning to a new firm decrease by roughly 2.1% for every additional percentage point difference in the separation risk between the two firms. The same intuition holds for the estimated firm effects Γ: a difference in firm amenities of 1 standard deviation increases the odds of accepting by 366% when differences in job security are not controlled for, and 297% otherwise. Moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the firm amenity distribution results in similarly large changes in the odds ratio of transitioning to a new job.

These numbers indicate that unobserved firm fixed effects play an important role in explaining job transitions between firms aside of observed income changes. To describe the value of these firm effects in monetary units, it is helpful to remember that the utility model 2 provides a conversion between the unobserved firm effects Γ and earnings in € in terms of the additional income that is necessary to make an employee indifferent between firms with different amenity estimates. Directly accounting for income in the choice model allows to scale the estimated amenity values back into monetary units[10].

Table 5 reports estimated statistics of the change in the firm amenities in monetary units for job transitions in the data set. Column 3 further controls for the difference in separation risk, analogous to column 3 of table 5. On average, job transitions lead to an increase in the amenity value of workers equivalent to an earnings increase of 24.9% (equivalently an increase of 0.223 units of log-earnings). Since the average change for job transitions in the data is 3.9%, the difference in amenities between firms amounts to 86% of the added utility in €-terms.

[10]This is the main conceptual advantage of the approach in Lehmann (2022) and this paper over the method pioneered in Sorkin (2018).

Table 4: Parameter estimates

	(1)	(2)	(3)
log(income)		2.478	2.478
separation risk			-2.108
Firm effect Γ			
Average	-0.0	-0.0	-0.0
Median	-0.063	-0.088	-0.118
Standard deviation	1.557	1.524	1.38
25th quantile	-0.991	-0.979	-0.858
75th quantile	0.905	0.861	0.736

Notes. The data used for estimating the coefficients of this table corresponds to the restricted and connected set described above.

Table 5: Amenities in monetary units

Change in amenities $\Delta\gamma$ / €	(1)	(2)	(3)
Average		0.262	0.223
Median		0.238	0.195
25th quantile		-0.166	-0.151
25th quantile		0.654	0.564
Firm effect Γ / €			
Average		-0.0	-0.0
Median		-0.036	-0.048
Standard deviation		0.615	0.557
25th quantile		-0.395	-0.346
75th quantile		0.348	0.297

Notes. The data used for estimating the coefficients of this table corresponds to the restricted and connected set described above. Amenities are further scaled to log-earnings. The top half of the table shows estimates of the change of amenities conditional on a voluntary job-to-job transition. The bottom half shows distributional statistics of the estimated firm amenity effects.

4.2 Life cycle effects

An established finding about job-to-job transitions is its role in earnings growth for young workers (Topel and Ward, 1992). Averages changes in log earnings through job-to-job transitions in figure 8 confirm these findings and show that younger workers experience a greater increase in compensation compared to their older colleagues. Earnings increases peak at 7% of current earnings for workers in their 20s, while workers in their 40s and 50s on average experience an earnings increase of only around 1%. In line with the literature, job-to-job transitions serve as an important catalyst for earnings growth at early career stages and diminish in their importance over the life cycle.

What was missing from the picture, however, is the fact that job-to-job transitions lead to disproportionate amenity increases among older workers. While the previous results indicated that general amenities of firms play a vital role in job transitions and contribute greatly to the welfare of all employees on average, segmenting the average amenity increase by age shows striking differences across age groups. Figure 7 displays the average amenity increase broken down by age. Employees in their 40s and 50s benefit the most from a transition to a new firm, with an amenity increase equivalent to 26-32% of their current earnings. On the other hand, the amenity increase experienced by those in their 20s is much lower with an average of 23% of their current earnings.

These findings suggest that the previous literature has understated the positive effects of job-to-job transitions on older workers. Once general firm amenities are taken into account, the benefits of switching employers extend beyond the early career stages. Summing up the contributions of amenities and income changes, effective welfare of job movers increases by more than 20% throughout their 20s, 30s and 40s, with an additional spike for workers aged around 50 and older.

Overall, amenities seem to matter far more for older workers at later stages in their career. An important caveat to keep in mind, however, is that older workers are also more likely situated on higher rungs of the general income ladder of jobs. Do the previous findings reflect a shift in preferences towards higher job quality as workers age? Or are amenities a luxury good, which workers value higher as their income increases? To test these two conflicting scenarios, I calculate the rank in the income distribution for each worker prior to their job-to-job transition to control for the effect of income. For the age of workers, I assign workers to three distinct cohorts, representing the young (younger than 35 years), the middle-aged (between 35 and 44 years) and the old (45 years and older). I do this, since figure 7 suggests that there are different stages in the age of workers with respect to amenity changes, and a linear control in age would not capture these stages well. I then run regressions of the form

$$\Delta\gamma/€_i \; = \; \alpha \; + \; \beta_{young}\mathbb{1}_{(age_i<35)} \; + \; \beta_{middle-aged}\mathbb{1}_{(35\leq age_i<45)} \; + \; \beta_{old}\mathbb{1}_{(age_i\geq 35)} \; + \beta_I \; earnings\_rank_i \; + \; \epsilon_i,$$

where *earnings_rank* is the percentile rank of the worker's earnings at the firm prior to the job-to-job transition. The results are reported in table 6. In the baseline regression, the amenities for the young cohort increase by an average of 23% in terms of earnings - or 0.208 in terms of log-earnings. For workers in the middle-aged cohort, the average amenity gain increases to 26% while the old cohort increases amenities by 32%. Controlling for different ranks in the earnings distribution only reduces the amenity increase marginally for all cohorts, indicating that income effects do not explain the effect. Moreover, the regression allows us to quantify the effect of moving to a higher income rank has on the expected amenity increase. A worker in the 75$^{\text{th}}$ percentile of the earnings distribution on average receives around 3.5 percentage points more additional welfare from amenities in terms of her previous income compared to a worker in the 25^{th} percentile - the estimate, however, is only statistically significant at the 10%-significance level.

My results on heterogeneity in firm amenities also matter for welfare inequality within cohorts. To this purpose, I use the full panel of workers employed by firms in the connected set - i.e. firms for which I have an estimate of amenities - and compute the variation of log-earnings as well as firm amenities for different age cohorts. The results are shown in table 7. While the within-age-cohort variation of log-earnings is almost identical for young, middle-aged and old workers, accounting for firm amenities reveals that welfare inequality inequality for older workers is 14% larger, indicating that workers move up the firm amenity ladder unevenly.

In this section I demonstrated that firm amenities are an important component of the benefits which workers derive from job-to-job transitions. The results suggest that as workers age, moving to firms that offer higher amenities becomes an important source of additional welfare as measured in log-earnings. In the next section, I will highlight why this discussion matters to a broader audience in the profession as it has implications for our fundamental understanding of earnings over the life cycle.

4.3 Amenities and earnings regressions

Dating back to Mincer (1958), economists and policy makers have used earnings regressions with polynomials in worker age - among other covariates - to describe and study the evolution of earnings over the life cycle. The empirical motivation for such a specification is apparent in figure 1, which shows that earnings increase quickly for young workers below the age of 35, while earnings of older workers increase little. The data is commonly explained in terms of returns to experience, as young workers are still accumulating human capital on the job, or in terms of reallocation to new occupations and firms. According to this narrative, young workers have steep a steep earnings curve, with frequent promotions and job changes which reflect high returns to additional experience and improvements in match quality at early career stages. As workers age, the earnings profile flattens significantly as subsequent jumps in earnings become less likely and workers are settling in their roles.

What the narrative misses out on, however, is the variation of amenities that firms offer to their workers. The estimates of the previous sections suggest that workers differentiate between firms on other factors rather than earnings alone, and that older workers are more likely to move up the amenity ladder. Thus, differences in amenities may be important for differences in welfare between old and young workers. The difference can be seen in figure 9. While log-earnings between the age of 25 and 55 increase by only 0.2 (implying a $\sim$ 22% increase in earnings), accounting for amenities doubles the difference to $\sim$ 0.4. Accounting for differences in firm amenities exacerbates welfare differences between young and old workers and also implies that older workers are more likely to achieve additional welfare gains that are missing from an analysis that focuses solely on earnings.

Motivated by these graphs, I estimate two Mincerian earnings regressions in table 8 - a traditional model, which captures the job value through log-earnings alone and an augmented model with log-earnings plus amenities as the dependent variable. In the augmented model, the job value increases more rapidly with age and firm tenure, two proxies of experience on the labor market. Interestingly, workers with a foreign nationality are more likely to be at low-quality firms, which reinforces existing welfare differences between native and foreign workers. Foreign workers are estimated to earn $\sim$ 11.2% less than native workers, but the difference in overall welfare increases to $\sim$ 28.3% after accounting for amenities.

5 Conclusion

In this paper, I apply a novel framework for estimating firm amenities by using job-to-job transitions in order to infer employee's revealed preferences over employers. I find evidence that workers move up the ladder of firms in terms of amenities, with larger jumps for workers of older age. Only a small fraction of the difference between young and old workers can be explained by income effects, while the rest represents fundamental life cycle effects. As a result, accounting for firm amenities explains why older workers more frequently take new jobs with equal or lower earnings compared to their younger peers.

Accounting for amenities also matters greatly for our understanding of inter-generational inequality. While the gap in earnings between workers in their mid-twenties and old workers in their fifties is at most 20%, accounting for firm amenities roughly doubles the difference to 40%.

A dimension that needs to be explored is worker heterogeneity. In experiments across the US, **?** find large differences in stated preferences and the willingness to pay for different job characteristics. While my results indicate changes in the amenity provision across the life-cycle, my framework cannot accurately distinguish between preference heterogeneity and alternative explanations such as liquidity constraints.

A key feature of the paper and the underlying methodology in Sorkin (2018) is that it treats amenities as a residual in explaining job transitions. It corresponds to the variation in firm values on which workers agree when choosing between employers, yet it offers no insights into what precisely constitutes the estimated firm values. On the one hand, this is an advantage as it allows to capture the effect abstract and immeasurable concepts such as company culture and management style. On the other hand, the method allows no inference which firm features matter to workers and therefore limits its applications in policy.

This paper lays the ground work to expand the method to account for further observable differences in measuring firm amenities and therefore gain a better understanding of what matters to workers. Since the data of this paper is anonymized, however, I only controlled for one specific dimension of firm amenities - job security - and found that around 15% of the amenity gain of job mobility can be explained by a move to a firm with more job security. Future research with more firm information would be highly relevant to understand key features of firms which workers find attractive.

Figure 7: Average change firm amenities after a J2J transition - log-earnings scale

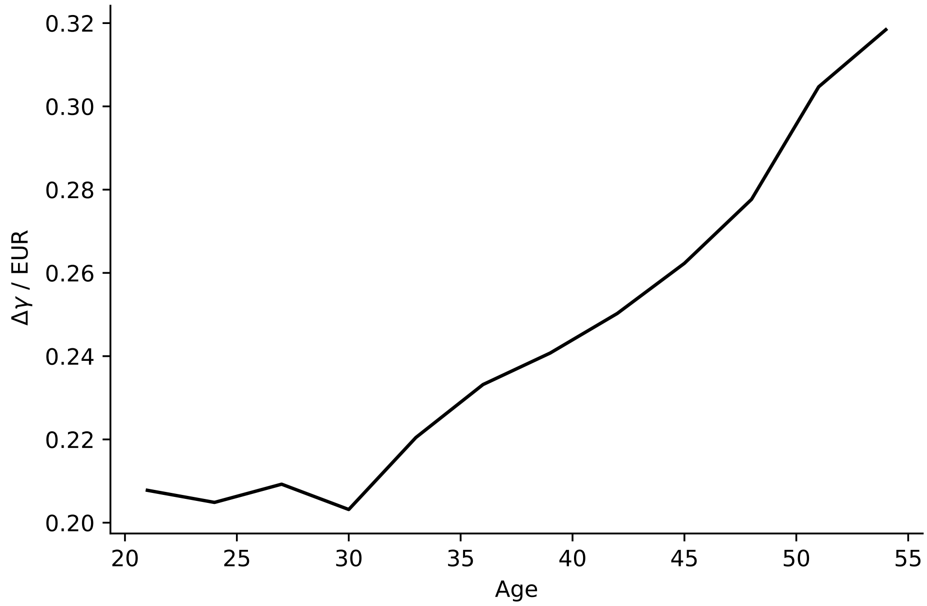


Figure 8: Average change in daily log-earnings after a J2J transition

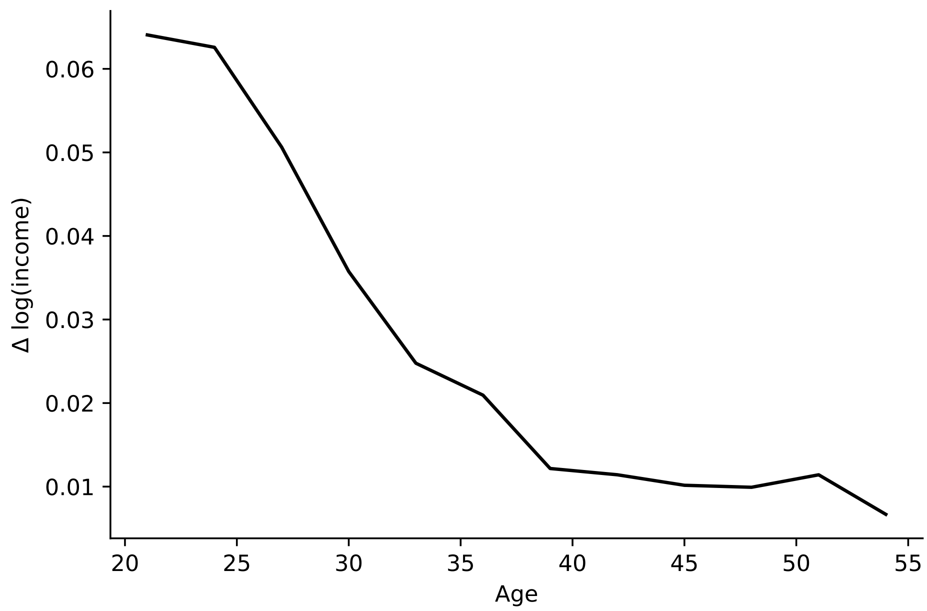
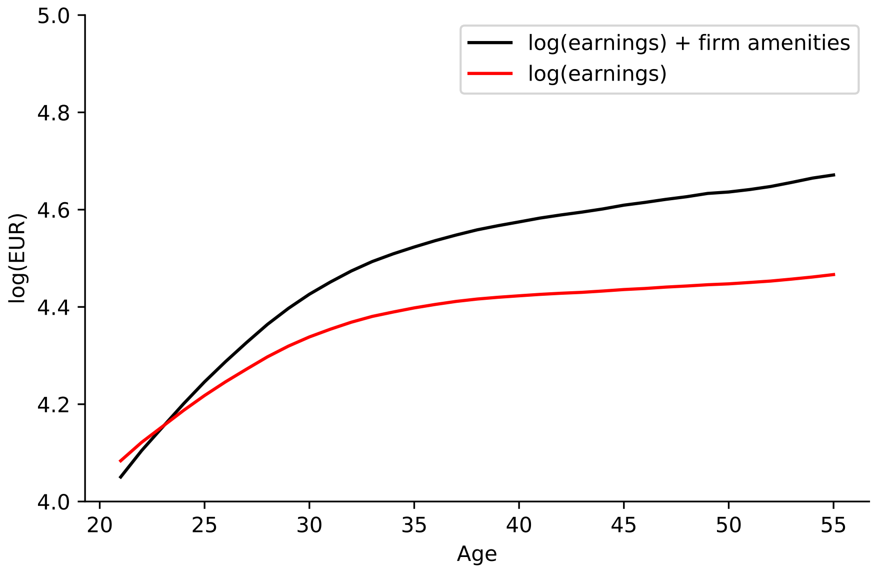
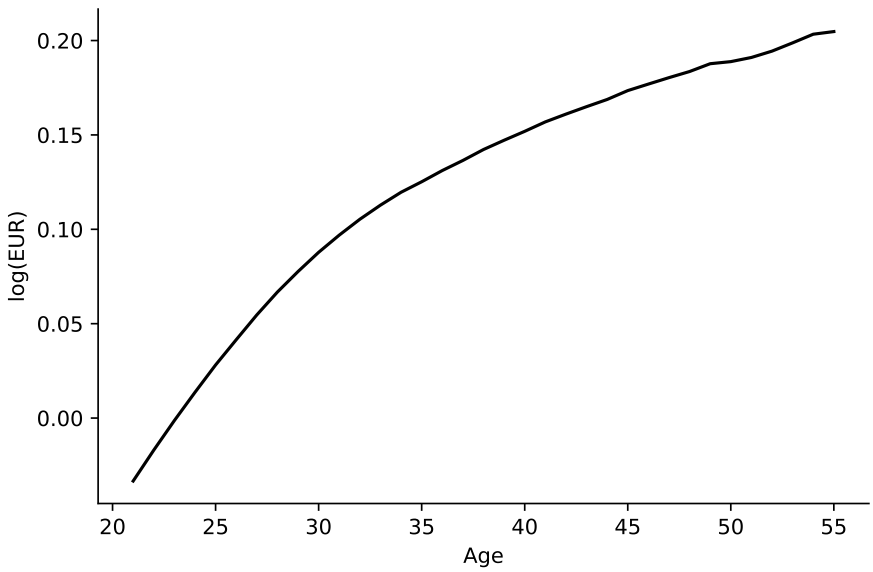


Figure 9: Implications of firm amenities for earnings regressions over the life cycle.



(a) Log-earnings of workers of different age over the life cycle without the value of firm amenities (red) and with the value of firm amenities (black).



(b) Average value of firm amenities by worker age in terms of log-earnings.

Table 6: Age vs. Income - What drives workers up the amenity ladder?

	Dependent variable: $\Delta\gamma$ / €	
	(1)	(2)
Age $<$ 35	0.208***	0.205***
	(0.001)	(0.002)
35 $\leq$ Age $<$ 45	0.233***	0.229***
	(0.002)	(0.003)
Age $\geq$ 45	0.277***	0.273***
	(0.003)	(0.004)
Earnings percentile		0.007*
		(0.004)
Observations	288,727	288,727
R^2	0.001	0.001
Adjusted R^2	0.001	0.001
Residual Std. Error	0.611(df = 288724)	0.611(df = 288723)
F Statistic	207.713*** (df = 2.0; 288724.0)	139.515*** (df = 3.0; 288723.0)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Cross-sectional distribution of earnings and firm amenities

All workers	(1)	(2)	(3)
Var(log-earnings)	0.09	0.09	0.09
Var(firm amenities)		0.39	0.30
Cov(log-earnings, firm amenities)		0.054	0.038
$Age < 35$			
Var(log-earnings)	0.083	0.083	0.083
Var(firm amenities)		0.362	0.276
Cov(log-earnings, firm amenities)		0.045	0.031
$35 \leq Age < 45$			
Var(log-earnings)	0.086	0.086	0.086
Var(firm amenities)		0.396	0.306
Cov(log-earnings, firm amenities)		0.050	0.034
$Age \geq 45$			
Var(log-earnings)	0.084	0.084	0.084
Var(firm amenities)		0.419	0.326
Cov(log-earnings, firm amenities)		0.054	0.0382

Notes. The data used in this table corresponds to the quarterly cross-section of employed male workers aged 21-55 in Austria between 1990 and 2009. Earnings are computed as average daily earnings. Employers which do not belong to the restricted and connected set are discarded. Amenities are scaled to log-earnings.

Table 8: Two types of earnings regressions

	log(earnings)	log(earnings) + amenities
Intercept	3.4627***	3.1167***
	(0.0006)	(0.0015)
Age	0.0376***	0.0563***
	(0.0000)	(0.0001)
Age^2	-0.0004***	-0.0006***
	(0.0000)	(0.0000)
Tenure	0.0129***	0.0166***
	(0.0000)	(0.0000)
Tenure^2	-0.0002***	-0.0003***
	(0.0000)	(0.0000)
foreign	-0.1069***	-0.2490***
	(0.0001)	(0.0003)
Observations	51,025,442	51,025,442
R^2	0.1656	0.0858
Adjusted R^2	0.1656	0.0858
Residual Std. Error	0.2739(df = 51025436)	0.6535(df = 51025436)
F Statistic	2025389.8706*** (df = 5.0; 51025436.0)	957737.6613*** (df = 5.0; 51025436.0)

Note: *p<0.1; **p<0.05; ***p<0.01

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A Descriptive statistics and plots

Table A.1: Aggregate firm statistics

Firms	All	Active	Larger
# of unique firms	1312392	796709	102114
Mean firm size	3.450	4.827	24.135
Mean daily earnings	31.829	32.340	58.562
Total Job-to-job transitions	5856922	5856922	3699707
Total Employment-to-unemployment transitions	4443891	4179243	2887476
Total Unemployment-to-Employment transitions	4764106	4496675	3173543

Notes. The sample includes all firms which employed a worker in Austria between 1990 and 2009. Definitions for the sub-samples are as follows. Active firms: any firm which hired a worker through a Job-to-job transition directly from another firm. Larger firms: any firm with at least 3 employees throughout the sample.

Figure A.1: Monthly Job-to-job transition rate (men) by quantile in the earnings distribution

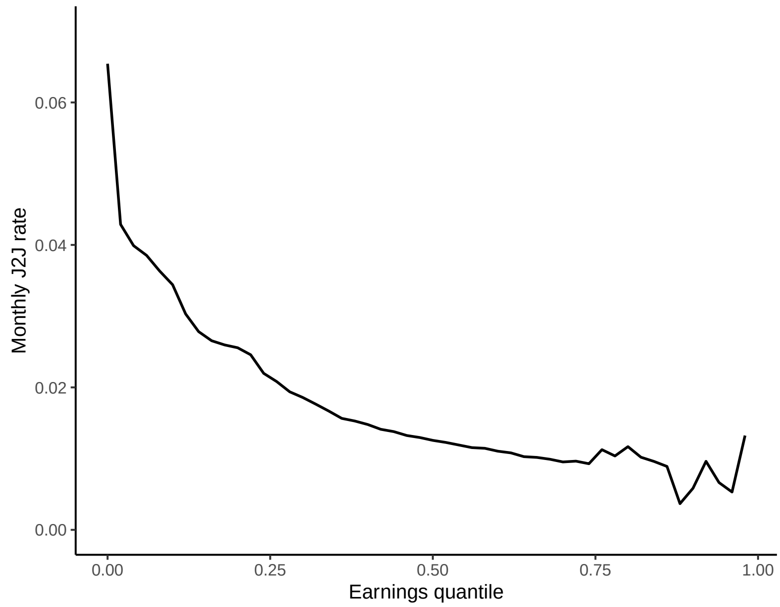

Figure A.2: Log income change by earnings quantile before job change

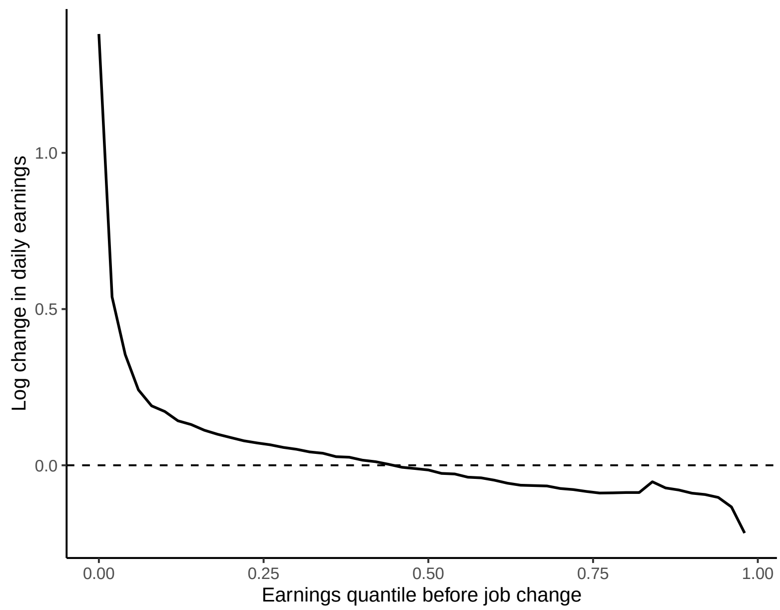

Figure A.3: Monthly transition rates over time

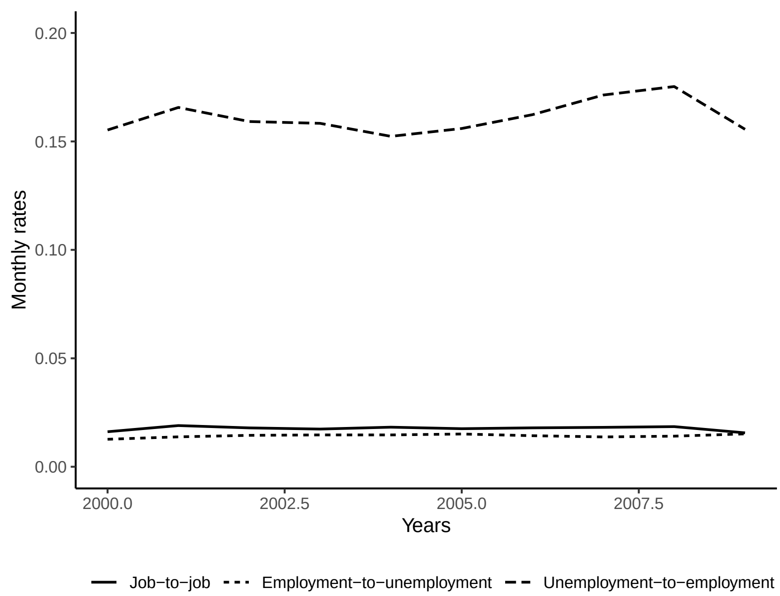

Figure A.4: Monthly employment-to-unemployment transition rate by age and gender

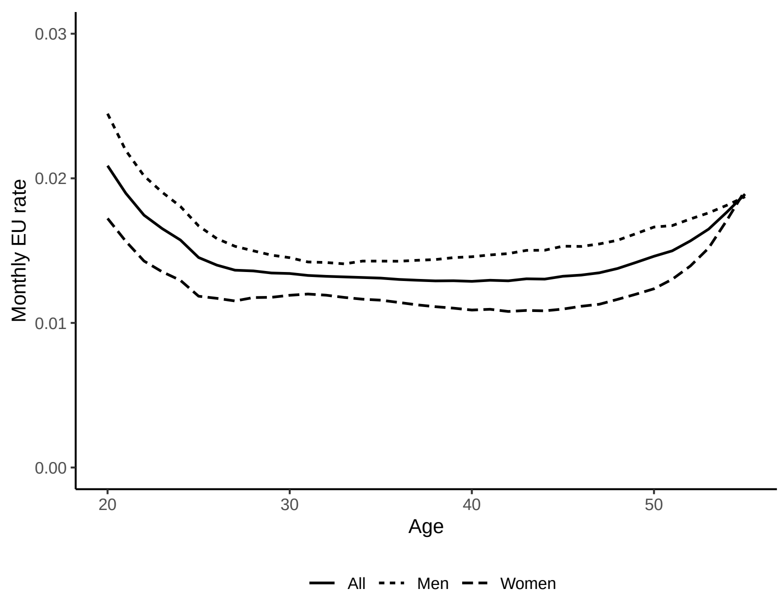

Figure A.5: Monthly unemployment-to-employment transition rate by age and gender

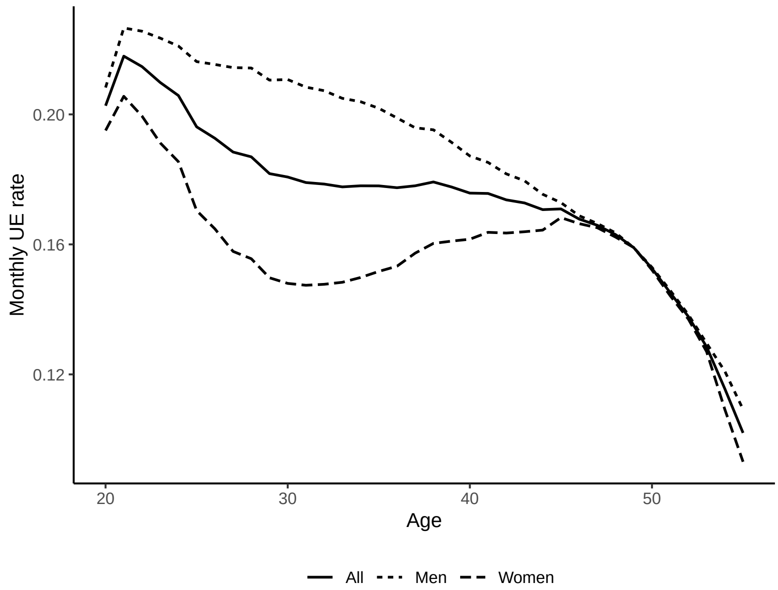

Figure A.6: Monthly EU, UE and J2J transition rates over time

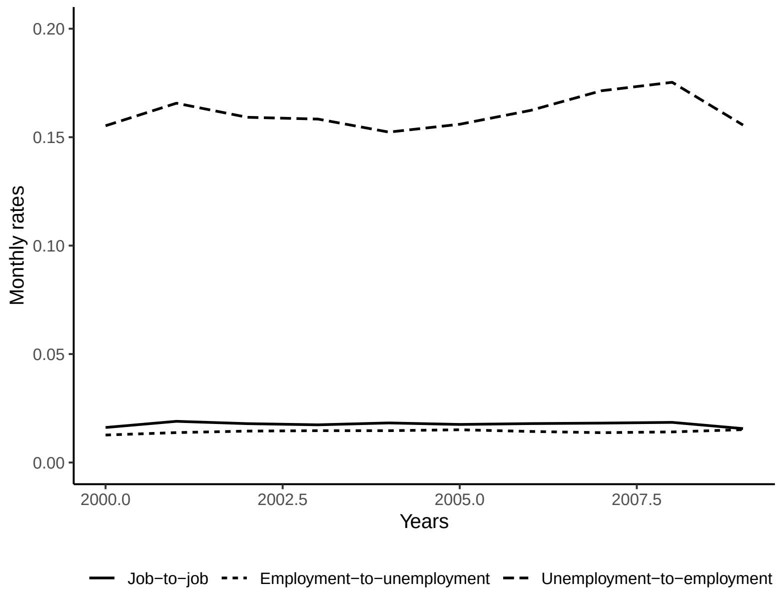

Figure A.7: Relationship between age, earnings rank and amenity change conditional on a job-to-job transition.