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ABSTRACT

Learning through Coworker Referrals*

In this paper, we study the role of coworker referrals for labor market outcomes. Using comprehensive Danish administrative data covering the period 1980 to 2005, we first document a strong tendency of workers to follow their former coworkers into the same establishments and provide evidence that these mobility patterns are likely driven by coworker referrals. Treating the presence of a former coworker in an establishment at the time of hiring as a proxy for a referral, we then show that referred workers initially earn 4.6 percent higher wages and are 2.3 percentage points less likely to leave their employers than workers hired through the external market. Consistent with a theoretical framework characterized by higher initial uncertainty in the external market but the possibility of subsequent learning about match-specific productivity, we show that these initial differences gradually decline as tenure increases. We structurally estimate the model using two different sets of auxiliary parameters and find that the noise of the initial signal about a worker's productivity is 14.5 percent lower in the referral market than in the external market, and that firms learn about their workers' true match-specific productivity with a probability of 48.4 percent per year. Counterfactual simulations show that average wages are 3.9 percent lower in the absence of a referral market, primarily because of lower average productivity in the external market.

JEL Classification: J31, J63, J64

Keywords: referrals, employer learning, networks, wages, turnover

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1 Introduction

Survey evidence from many countries in the world consistently shows that between a third and half of all jobs are found through social contacts. One important mechanism through which such contacts can facilitate the job search process is by means of a referral. Referrals provide employers looking to fill a vacancy with information about potential applicants that they otherwise would not have. Workers hired as the result of a referral are therefore likely to be better matched to their employers than workers hired through more formal channels.[1]

In this paper, we study the role of referrals for workers' labor market outcomes. To motivate our empirical analysis, we present a stylized theoretical search model that is characterized by initial uncertainty and subsequent learning about workers' match-specific productivity. Firms can hire workers either through the referral market or through the external market. When workers and firms meet, they observe a noisy signal of their true match-specific productivity, which is assumed to be less precise in the external market than in the referral market. As a result of this lower uncertainty, workers hired through a referral are initially better matched to their employers, which is reflected in higher starting wages and an initially lower probability of separating again from the hiring firms. Due to learning and successive separations of bad matches, these initial wage and turnover differences decline as tenure in the firm increases.

In the empirical part of the paper, we then test the dynamic predictions of our theoretical model using comprehensive Danish administrative data covering the period 1980 to 2005. Since actual referrals are not observed in this type of data, we use a proxy that is based on the observation that, through coworker-based referrals, workers have a tendency to start their new jobs in firms in which a former coworker is already present. We first document that this type of mobility pattern is indeed linked to the prior personal interaction of workers and cannot be explained by random mobility or similarity in observable skills between workers and their former colleagues. Building on this result, we use an indicator for starting a new job in a firm with a former coworker already present as a proxy for having obtained the job through the referral market, and estimate non-parametric convergence profiles for both wages and job turnover probabilities as a function of tenure.

Our empirical analysis yields a number of results. First, we find that the probability of starting a new job in a firm with a former coworker already present is significantly higher than would be expected under a random allocation of workers to firms, both unconditional and conditional on workers' observable skills. This finding lends support to our assumption that the presence of a former coworker in the new firm of a worker can serve as a proxy for having obtained the job through a referral. Our main estimation results show that, in the first year after being hired, workers recruited through the referral market earn 4.6 percent higher wages and are 2.3 percentage points less likely to leave their employer than workers hired through the external market. As predicted in the presence of learning about match-

[1] Topa (2011) provides a comprehensive summary of the literature on the use of referrals in the labor market. Oyer and Schaefer (2011) survey the literature in personnel economics on firms' recruiting strategies including the use of employee referrals.

specific productivity, these differences gradually decline over time and stabilize in the long run, with most of the learning taking place within the first six years. We then show that the main mechanism driving these convergence patterns is the more pronounced weeding-out process of bad matches among the group of workers hired through the external market. In contrast, the contribution of differential wage growth among workers who remain with their hiring firms in the long run is relatively limited.

To complement our main findings, we show that referrals from coworkers with whom prior interaction was more intensive tend to amplify the initial wage and job stability gains and are thus particularly valuable in the job search process. Distinguishing workers with different levels of education reveals that the initial wage gains are more pronounced for high-skilled workers, which suggests that the initial uncertainty about the skills of these types of workers is larger, possibly because of the more complex jobs they tend to fill. This hypothesis is also consistent with the slower speed of learning we find in our structural estimation for high-skilled workers in comparison to low-skilled workers. Corresponding results for workers belonging to different age groups do not show major differences in initial wages and turnover probabilities but suggest that young workers hired through the referral market have on average a lower productivity than their counterparts hired through the external market.

In the second part of the paper, we estimate the structural parameters of our model by indirect inference, matching the tenure-specific empirical moments from the reduced-form estimations to their simulated model counterparts. The estimates reveal that the uncertainty about match-specific productivity in the referral market is around 14.5 percent lower than in the external market, indicating that referrals provide additional information to hiring employers. Furthermore, our findings show that learning takes place at a relatively fast pace, with a 48.4 percent probability that a worker's true productivity is revealed in any given year. While matching the overall convergence patterns well, the baseline model does not provide a good fit for the difference in wages between referred and externally hired workers at high levels of tenure, which is the primary statistic identifying the average difference in the underlying productivity distributions. We therefore estimate an alternative model, which puts more weight on these long-run differences in wages. Using this model, which fits this feature of the data well, we estimate that the average match-specific productivity of workers in the referral market is about 7.6 percent higher than in the external market, suggesting that referrals allow firms to tap into a better pool of job applicants. To conclude, we use the model to perform counterfactual simulations, which show that average wages are 3.9 percent higher due to the existence of a referral market, primarily because of higher average productivity in the referral market and, to a lesser extent, differences in uncertainty.

The particular focus on referrals by former coworkers in our analysis is motivated by the important role these types of referrals seem to play in the labor market (see, e.g. Granovetter, 1995). In a recent study, Eliason et al. (2017) exploit rich Swedish administrative data to provide the first comparative evidence on the relative importance of different types of social networks for individual labor market outcomes, documenting a prominent role for former coworkers that is only surpassed by that of immediate family members. Presumably, the usefulness of coworkers as providers of referrals (as in Montgomery, 1991, Simon and Warner, 1992, Galenianos, 2013) or sources of information about available job opportunities (as in Calvó-Armengol and Jackson, 2004, Wahba and Zenou, 2005, Boucher and Goussé, 2019) is due to the fact that, by having worked together in the past, coworkers tend to possess better knowledge about their social contacts' respective skills and are more aware of suitable job openings than other types of social contacts such as former classmates, friends or neighbours, who often lack the professional interaction on the job and the attachment to the relevant labor market segment (see Antoninis, 2006).[2] In recent years, a number of studies have therefore analyzed in more detail this type of social connection and its role for labor market outcomes (see, for instance, Cingano and Rosolia, 2012, Hensvik and Skans, 2016, Glitz, 2017, Saygin et al., 2019).

Contrary to much of this literature, which has focused on the role of coworker-based networks in increasing job offer arrival rates (Cingano and Rosolia, 2012, Glitz, 2017, Saygin et al., 2019), we study the role of *coworker-based* referrals in reducing information frictions in the hiring process. Our empirical work is guided by a Jovanovic-type learning model, initially adapted to the referral context by Simon and Warner (1992) and then substantially extended by Dustmann et al. (2016), in which initial uncertainty coupled with subsequent learning about match-specific productivity is generating distinct patterns of wages and job turnover as a function of tenure. Our empirical analysis is closely related to the work by Dustmann et al. (2016), Brown et al. (2016), and Burks et al. (2015) who study the main predictions of the same learning model but follow different strategies than ours to identify jobs that have been obtained through a referral. The main analysis in Dustmann et al. (2016) relates the share of *co-nationals* in a firm located in a large metropolitan area at the time of hiring to a worker's subsequent labor market outcomes and provides both a theoretical and empirical link between this share and the likelihood of having obtained the job through a referral, allowing the estimated effects to be translated into referral effects. In addition, they also provide some evidence using actual referrals by linking the responses from a recent survey to the German administrative data. However, the number of observations in this linked data set is relatively small so that the scope of the analysis based on actual referrals remains relatively limited. Both Brown et al. (2016) and Burks et al. (2015) use data on actual referrals from a single or small number of large firms to test the predictions of the learning-based model against other types of labor market referral models.

Our analysis contributes to this literature in a number of ways. First, we are the first to systematically analyze the role of coworker-based referrals within the learning-based model framework of Simon and Warner (1992) and Dustmann et al. (2016). Given the importance of coworker-based referrals in many labor markets around the world, it is important to

[2] Recent studies that have analyzed the role of neighborhood-based networks for individuals' labor market outcomes include Bayer et al. (2008), Hellerstein et al. (2011), Damm (2014), and Schmutte (2015). Recent studies focusing on the role of former classmates and friends include Marmaros and Sacerdote (2002) and Cappellari and Tatsiramos (2015). Kramarz and Skans (2014) is one of the few empirical studies that explicitly analyzes the role of family-based networks in the labor market.

understand how they affect labor market outcomes and whether their role differs from that of other types of referrals. Second, in contrast to existing studies, our analysis is representative for an entire national labor market. Third, because of the large sample sizes, we can test the predictions of the learning-based model in a more comprehensive way than existing studies, for example regarding the precise shape of the convergence profiles and the role of different mechanisms in generating these profiles. Fourth, we are the first to perform a full structural estimation of the model parameters of interest, shedding light on important features such as the speed of learning, average match-specific productivity and the degree of uncertainty about workers' skills in different markets. Because we have population-wide data, we can estimate the model for different socioeconomic subgroups and compare the precisely estimated parameters. Since, contrary to many other network dimensions, coworker relationship are nowadays readily observable in most administrative data sets, our analysis can provide a foundation for future work on this topic, both theoretical and empirical.

The paper is structured as follows. In the next section, we present the main features of our theoretical framework. We then discuss our econometric model in Section 3. In Section 4, we provide information about the data used in the empirical analysis and summarize their main features. In Section 5, we show evidence that speaks to the appropriateness of using the presence of former coworkers as a proxy for a referral. In Section 6, we present our main empirical results. Finally, in Section 7, we describe the calibration and summarize the key findings from our structural model estimation. Section 8 concludes the paper.

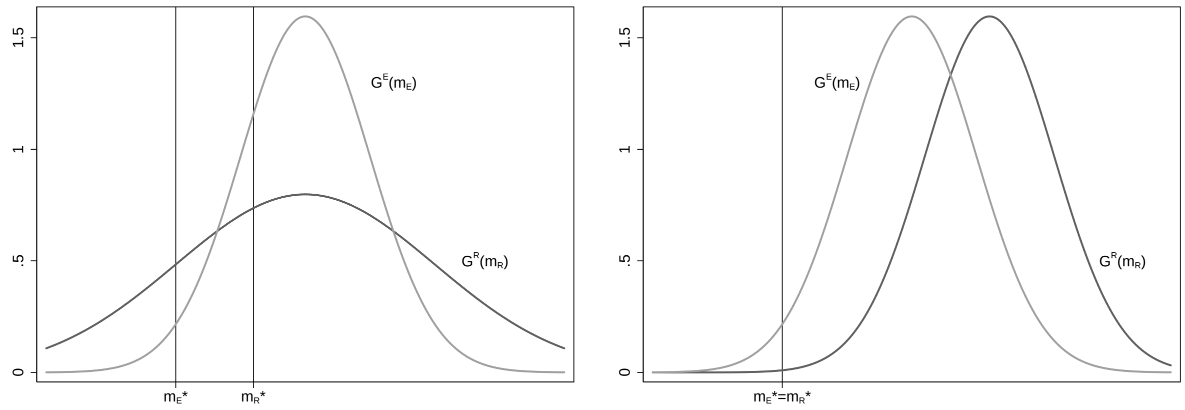
2 Theory

To motivate our empirical analysis, we use a stylized model of the labor market in the spirit of Jovanovic (1979), Simon and Warner (1992) and Dustmann et al. (2016). In this section, we only provide the main features of the model. The full model, derivations, and solutions can be found in Appendix A. In our model, workers search for new jobs while being unemployed. They can get job offers from two distinct markets, the external (E) and the referral (R) market. When workers and firms meet through market $k = \{E, R\}$, they receive a noisy signal about their match-specific productivity, $\widehat{y}_k = y_k + \varepsilon_k$, where the true match-specific productivity y_k comes from a normal distribution with mean $\overline{y}_k$ and variance σ_y^2 and the noise term ε_k is drawn from a normal distribution with mean zero and variance σ_k^2. After observing the noisy signal $\widehat{y}_k$, workers and firms form an expectation about their match quality, which we denote by $m_k = E(y|\widehat{y}_k, k)$, based on which they then decide whether or not to form a match.[3] If a match is formed, workers are being paid their expected productivity.

After the initial period, firms learn at a rate α about the true match-specific productivity of a worker. If this productivity is sufficiently high, the employment relationship continues

[3]The expected match-specific productivities m_k are normally distributed with mean $\overline{y}_k$ and variance $\frac{\sigma_y^4}{\sigma_k^2+\sigma_y^2}$. In the theoretical derivations, we denote these distributions by G_k.

Figure 1: Expected Match-specific Productivity Distributions



(A) $\sigma_R^2 < \sigma_E^2, \quad \overline{y}_R = \overline{y}_E$ (B) $\sigma_R^2 = \sigma_E^2, \quad \overline{y}_R > \overline{y}_E$

and the worker is being paid according to his productivity. If the true match-specific productivity is too low, workers and firms separate and the worker becomes unemployed. In addition to these endogenous separations, employed workers experience an exogenous job destruction shock at rate δ.

The key distinction between the two markets is that the signal in the external market is more noisy than the signal in the referral market, $\sigma_R^2 < \sigma_E^2$, reflecting the fact that referrals provide information to prospective employers that they otherwise would not have.[4] In addition, there could be differences in the average match-specific productivity $\overline{y}_k$ in the two markets, for example because workers in the referral market are, on average, of higher productivity than workers in the external market.

The first main theoretical result arising from this framework is that, at the hiring stage, the reservation expected match quality in the external market is lower than the corresponding reservation expected match quality in the referral market, $m_R^* > m_E^*$. The intuition is that, due to the higher uncertainty, there is more scope for future wage growth for workers hired through the external market as they are partially insured against low realizations of their match-specific productivity by quitting their job. As a result, workers hired through the external market are willing to accept wage offers that otherwise identical workers hired through the referral market would turn down. If $\overline{y}_R \geq \overline{y}_E$, this implies that the average wages of workers hired through the referral market are initially higher than the average wages of workers hired through the external market.

Figure 1 illustrates the distributions of expected match qualities in the referral and external market, which we denote by $G_R(m_R)$ and $G_E(m_E)$. The left panel shows the situation where $\sigma_R^2 < \sigma_E^2$ and $\overline{y}_R = \overline{y}_E$. Since $m_R^* > m_E^*$, it is clear that the truncated mean of $m_R | m_R \geq m_R^*$, which corresponds to the average initial wage of workers hired through the referral market, is larger than the truncated mean of $m_E | m_E \geq m_E^*$, the average initial

[4]In this section, we assume that $\sigma_R^2 < \sigma_E^2$ to illustrate how the model works. However, in the estimation later on, we do not impose this assumption but leave σ_R^2 and σ_E^2 unrestricted.

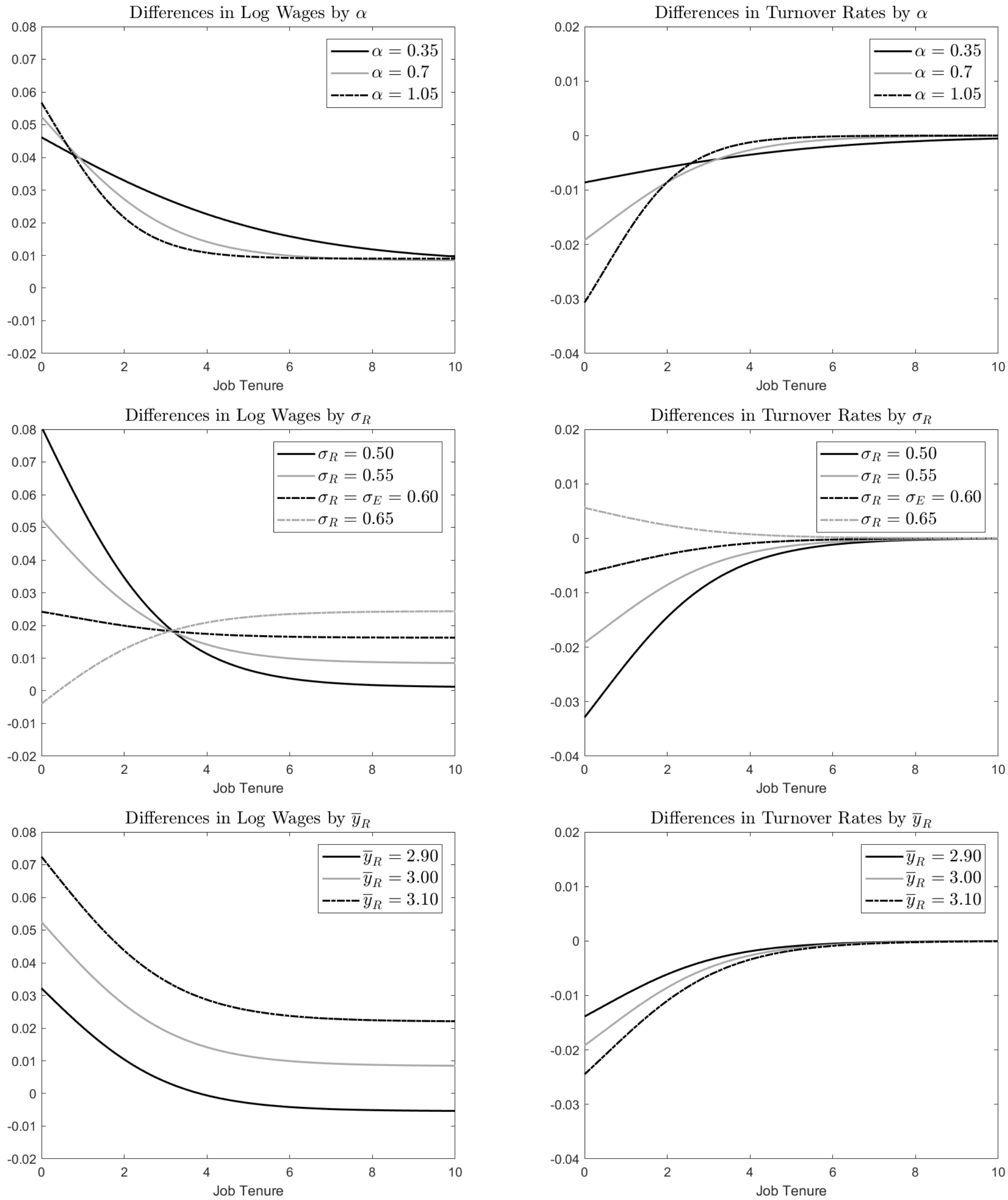
wage of workers hired through the external market. The right panel of Figure 1 displays the situation when $\sigma_R^2 = \sigma_E^2$ but $\overline{y}_R > \overline{y}_E$. Since in this case, the reservation expected match-specific productivity is identical in both markets, a comparison of the two truncated distributions immediately shows that the average initial wage of workers hired through the referral market is once again higher than the average initial wage of workers hired through the external market.

The second main theoretical result relates to the evolution of the wage and turnover differences as tenure increases between workers hired through the referral market and workers hired through the external market. Over time, match-specific productivity is revealed and workers with productivity below a certain reservation match quality y^*, which is independent of the channel through which a worker was hired, separate from the firm. Since externally hired workers are on average less well matched to their firms initially, this weeding-out process of the least-able workers is more pronounced among workers hired through the external market. As a result, the initial average differences in wages and turnover probabilities between referred and externally hired workers decline over time and, in the case of turnover, necessarily converge to zero. This is because, after all information has eventually been revealed, the only source of job separations is the exogenous job destruction rate δ which is assumed to be independent of the channel through which a worker was hired. For wages, there is a second mechanism besides the differential weeding-out process that affects wage profiles in the referral and external market: even for identical workers whose true match-specific productivity is above the threshold y^*, wage growth will be stronger if they are hired through the external market. This can be easily seen in the extreme case of no uncertainty in the referral market, in which case a referred worker will have a constant wage rate throughout his employment spell while an externally hired worker will, on average, start with a lower wage but receive a wage increase once his true productivity is revealed.

To illustrate the key empirical patterns of our model and their dependence on key structural parameters, Figure 2 depicts relative wage and turnover profiles based on simulations of our model in which we vary one structural parameter and fix the remaining ones at values similar to those we eventually estimate in Section 7. The upper two panels show how the differences in wages and turnover probabilities between the referral and external market decline with tenure and how the speed of this convergence process depends on α, the speed of learning about true match-specific productivity in the model. Note that contrary to the long-run difference in relative turnover probabilities, which converges to zero for all values of α, the long-run difference in wages converges to a positive value, reflecting the fact that average productivity is higher in the referral than in the external market (3 vs. 2.881).

The middle panels depict relative wage and turnover profiles for different values of σ_R, the standard deviation of the noise in the referral market. As already discussed, the less uncertainty there is in the referral market, the higher is the initial wage and turnover gap relative to the external market. However, while the relative turnover rate once again converges to zero in the long run as in the case with different α values, the difference in uncertainty in the referral and external market has implications for the long-run difference

Figure 2: Differences in Log Wages and Turnover - Simulation



Note: To derive these wage and turnover profiles, we use the following baseline parameterization: $\sigma_E = 0.6$, $\sigma_R = 0.55$, $\sigma_Y = 0.1.332$, $\lambda_E = 4.603$, $\lambda_R = 1.175$, $b = 2.505$, $\delta = 0.204$, $r = 0.05$, $\alpha = 0.7$, $\overline{y}_R = 3$ and $\overline{y}_E = 2.881$. The parameters are approximately set to the values that we estimate in Section 7 in a full structural estimation.

in wages, too. In particular, the smaller σ_R relative to σ_E, the smaller is the long-run difference in wages.[5] The reason for this maybe somewhat surprising finding is again best understood in the extreme case of no uncertainty in the referral market. In this case, every referred worker whose true match-specific productivity lies above y^* will end up being hired. In contrast, there will be some workers with true match-specific productivity above y^* who, due to a sufficiently large negative signal, will not be hired through the external market, especially when their productivity is relatively close to y^*. As a result, there will be a lack

[5] Note that the relative wage profile is not flat when $\sigma_R = \sigma_E$ because the average productivity in these simulations differs between the referral and external market ($\overline{y}_R = 3$ and $\overline{y}_E = 2.881$). If they were the same, the profile would indeed be flat and the difference equal to zero throughout.

of mass of externally hired workers with true match-specific productivity above y^* in the long run, pushing up their average wages relative to those of referred workers.[6]

The bottom two panels show how the relative wage and turnover profiles vary with the average match-specific productivity in the referral market ($\overline{y}_R$) relative to the external market ($\overline{y}_E$). While the relative turnover profiles once more show the familiar pattern of long-run convergence to zero independent of the difference in average productivity, the relative wage profiles shift up in a parallel fashion the larger the average productivity gap in the two markets. In Section 7, we discuss in more detail how the predicted patterns depicted in Figure 2 contribute to the identification of the structural parameters of interest.

3 Econometric Model

In this section, we describe how we estimate the dynamic wage and turnover profiles that are at the center of our theoretical framework. Our main estimation equation is given by

$$y_{it} = \alpha + \beta_0 CW_{i\tau} + \beta_1 (CW_{i\tau} \times \text{Tenure}_{it}) + X_{it}'\theta + \gamma_t + \phi_f + \varepsilon_{it}, \tag{1}$$

where y_{it} are either log wages or an indicator for having left the current establishment by period $t+1$, and $CW_{i\tau}$ is an indicator variable taking the value 1 if worker i started the current job in an establishment with at least one former coworker present at the time of entry τ (when $\text{Tenure}_{it} = 0$). Interpreting the presence of a former coworker as a proxy for a referral, the parameter β_0 then reflects the initial gap in wages and turnover probabilities of workers hired through the referral market relative to workers hired through the external market. Due to the higher initial expected match quality, we expect β_0 to be positive in the wage regressions and negative in the turnover regressions. The parameter β_1, in turn, captures how the differences in wages and turnover probabilities evolve over time as tenure increases. Because of continuous learning about match-specific productivity and selective separations, we expect the initial differences to decline, implying a negative β_1 in the wage regressions and a positive β_1 in the turnover regressions.

In our estimations, we also include a vector of individual and establishment characteristics X_{it}, a full set of year fixed effects γ_t and, in the preferred specification, a full set of establishment fixed effects ϕ_f. The additional regressors in X_{it} are tenure, tenure squared, age, age squared, total accumulated experience, total accumulated experience squared, occupation-specific experience, occupation-specific experience squared, log establishment size, industry dummies, education group dummies, a gender dummy, and a dummy for being an immigrant. Importantly, all dummies are interacted with tenure and tenure squared to ensure that our estimates of β_0 and β_1 are not driven by heterogeneous tenure profiles across socioeconomic

[6] While positive signals may initially lead to workers with match-specific productivity just below y^* being hired through the external market, these workers will eventually separate again from their firms once their true productivity is revealed.

subgroups that rely differentially on referrals in their job search process. We also include a dummy for having been hired before 1991, interacted with tenure and tenure squared, since for these workers, due to the way our measure of coworker relationships is constructed, we do not observe whether they started their current job through the referral or external market (see Section 4 for details). Since they contribute to the estimation of many parameters related to the control variables, in particular the establishment fixed effects, we decided to include these workers in the estimation sample rather than drop them entirely but treat them as a separate group. Contrary to Dustmann et al. (2016) but similar to Burks et al. (2015) and Brown et al. (2016), we do not include worker fixed effects in our specification since the parameters of interest would then be estimated from a relatively limited set of observations and, by construction, rely on variation in wages and turnover probabilities at very different stages of a worker's career, allowing life-cycle effects to potentially confound the estimation.[7]

Our vector of control variables X_{it} includes an extensive set of controls for a worker's prior labor market experience, both in terms of general experience, which is real accumulated experience and not just potential experience, and occupation-specific experience, measured by the accumulated number of years a worker has worked in the current occupation, distinguishing between 90 occupations.[8] Controlling adequately for labor market experience is important in the present context, since having accumulated more experience in the past, both general and occupation-specific, is likely to be associated with a larger set of former coworkers and hence a higher chance of starting a new job in an establishment with one of these workers present. The regressor $CW_{i\tau}$ could then just be a proxy for accumulated work experience. This would be particularly problematic since in that case, due to the concavity of the typical wage-experience profile, the parameters β_0 and β_1 would likely have the same signs as those predicted by our theoretical model: higher initial wages and job stability for more experienced workers but also slower wage growth and changes in turnover probabilities in the periods thereafter.

After estimating equation (1) parametrically, we estimate in a second step a semi-parametric version of this model in which we replace all experience measures (tenure, age, accumulated experience, accumulated occupational experience) and their squared terms with a fully flexible vector of dummy variables. Crucially, this allows the effect of being hired through a referral to evolve non-linearly with tenure, a prerequisite for any type of long-run convergence profile.[9] Rather than reporting the full set of estimates from these semi-

[7]In addition, in the turnover regressions with worker fixed effects, the required assumption of strict exogeneity of the key regressors of interest is questionable since current shocks to job turnover are likely to be correlated with the future probability of working together with a former coworker. Controlling for heterogeneity in workers' productivity by including estimated worker fixed effects from a fully-specified wage equation leads to largely comparable results as in our main specification.

[8]Occupation-specific labor market experience is right-censored since the occupational variable is only included in the data from 1991 onwards.

[9]To keep the number of regressors manageable, we continue to interact the year, industry, gender, education and immigrant dummies with tenure and tenure squared only rather than the full vector of tenure dummies.

parametric regressions, we will present the main results visually by plotting the estimates for different values of tenure.

4 Data

The basis of our empirical analysis is the Danish matched employer-employee data set IDA, which contains annual cross-sectional information on the entire population in Denmark aged 15 to 70 as well as identifiers and limited background characteristics of the establishments in which individuals work.[10] Besides a variety of socioeconomic variables, the data comprise a number of labor market characteristics, including a worker's average yearly hourly wage rate for the job occupied in the last week of November. Throughout the paper, we restrict the data to the period 1980 to 2005 since municipalities in Denmark underwent a profound reform in 2006, reducing their number from 271 to 98. As a consequence of this restructuring process, the address codes Statistics Denmark uses to generate workplace identifiers changed, resulting in many workplaces being assigned new identifiers in 2006.[11] We further restrict the sample to individuals of primary working age 25 to 54.

We define individual i's network of former coworkers at time t as the set of all workers this individual has worked with during the previous 10 years (but not the current year):

$$\mathbb{C}(i) \equiv \{k \neq i : \sum_{q=t-10}^{t-1} \mathbf{1}(f_{kq} = f_{iq}) \geq 1\},$$

where f_{kq} is the establishment identifier for individual k at time q. Since we aim to pick up personal interactions between any two individuals, the construction of coworker networks is based on common employment spells in the same establishments.[12] To ensure that, prior to finding the new job, each worker had a period of ten years available during which to build up his network of former coworkers, the first period included in our estimation sample is 1991. While we use all available worker observations in our regressions, what identifies the shape of the wage and turnover convergence profiles in our estimations are only those workers who start a new job at a new establishment during the sample period.[13] Overall, we observe 4,487,111 job starters between 1991 and 2004.

Table 1 contains some descriptive statistics on these workers as well as their networks of former coworkers. At the time of moving into their new job, workers have on average 10.7

[10] The *Integreret Database for Arbejdsmarkedsforskning* (Integrated Database for Labor Market Research) is constructed and maintained by Statistics Denmark.

[11] Apart from the issue of changing workplace identifiers after 2005, there is also a dynamic inconsistency in the data when Statistics Denmark allowed so-called fictitious workplaces of e.g. sailors, sales representatives, and temporary workers to exist to a higher degree from 1991 onwards. As a result, the share of workers employed in these fictitious workplaces increased from approximately 1 percent before 1990 to 4-5 percent after 1990. We treat workers in fictitious workplaces as working alone.

[12] The establishment identifier is constructed by Statistics Denmark and is maintained across years if one of three criteria is met: same owner and industry; same owner and workforce; same workforce and either same address or same industry.

[13] We do not include workers who find a new job in 2005 since for these workers the turnover outcome variable is missing.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	5^{th} Percentile	Median	95^{th} Percentile
Individual Characteristics					
Share Female	46.3	49.9	0	0	1
Share Immigrant	5.8	23.4	0	0	1
Share Some High School	24.2	42.8	0	0	1
Share High School/Vocational Training	50.0	50.0	0	0	1
Share College Education	25.8	43.8	0	0	1
Age	36.3	8.3	25	35	51
Labour Market Experience	10.7	7.4	1.1	9.2	25.1
Occupational Experience	2.2	2.7	0	1	8
Network Characteristics					
No. of Former Coworkers	959	1,761	15	299	4,164
Duration of Collaboration	1.8	1.5	1	1	5
Years Since Separation	5.2	2.8	1	5	10
Share Working With ≥ 1 Coworker	33.3	47.1	0	0	1
of which ≥ 1 Incumbent Coworker	65.1	47.7	0	1	1

Note: All shares given in percent. Variables "Duration of Collaboration" and "Years Since Separation" summarized across worker-coworker observations. Sample size 4,487,111.

years of total labor market experience in Denmark and 2.2 years of accumulated experience in the particular occupation associated with the new job. The size of the networks that workers established over the previous ten years is large, with on average 959 former coworkers. However, this distribution is strongly right skewed, with a median of only 299 coworkers. While it may be questionable that a given worker would be able to maintain contact with such a large number of former coworkers, the administrative nature of the data and absence of information about actual social interactions does not allow us to further isolate the relevant part of the coworker network without making ad hoc assumptions on who stays in touch with whom based on observable worker characteristics. We therefore prefer working with the entire network of former coworkers, but we will test for heterogeneity in our estimates due to differences in the intensity of social interaction between workers, which we proxy by either the duration of the common employment spells or the time passed since workers separated from each other. As Table 1 shows, the average duration of common employment spells in the data is 1.8 years and the average number of years that have passed since separation from a given coworker is 5.2 years, with substantial variation in these two measures that can be exploited to define sub-components of a worker's coworker network with which social contact is likely to be more intense. As shown in the penultimate row of Table 1, a third of all workers start working in a job with at least one former coworker already present.

For the final estimations, we impose a number of further restrictions on the sample of workers who start a new job during the sample period. First, we exclude workers with a network size beyond the 99th percentile of the network size distribution as these are workers who used to work in the largest establishments in Denmark and it is unreasonable to assume all their coworkers would form part of their network. Second, for the indicator $CW_{i\tau}$ to equal one, we require that at least one of the former coworkers present in the new establishment is an "incumbent" former coworker, i.e. a worker who was already observed working in that same establishment in the previous period. This is to rule out cases where two former coworkers arrive in a new establishment at the same time which would make a determination of the referral direction impossible. For the indicator $CW_{i\tau}$ to equal one, we further require that the focal workers do not arrive together with more than four other coworkers from their previous employer as such joint movements of workers from one establishment to another are likely due to other reasons than individual referrals such as mergers or firm acquisitions.[14]

5 Referral Proxy

In the absence of direct information on whether a job was obtained through a referral, we assume that when a worker follows a former coworker into the same establishment, this new job was obtained through a referral. However, while a typical referral would give rise to this type of mobility pattern, there are other reasons for why former coworkers may end up working together again at the same employer that have nothing to do with the use of referrals. One such reason is pure coincidence. As documented in Table 1, networks of former coworkers tend to be large. Even in the absence of a real personal link between any two workers, they may work in the same establishment in the future, simply because of the thinness of the labor market and the limited number of jobs around. In addition, workers who used to work in the same establishment often share similar characteristics which makes them more likely to look for new jobs at the same set of employers.

To assess how much of the propensity of workers to follow their former coworkers into the same establishments can be explained by randomness and similarities in observable characteristics, we rely on an empirical approach that has been widely used to measure the systematic extent of ethnic segregation in the labor market (see Carrington and Troske, 1997, Hellerstein and Neumark, 2008, or Glitz, 2014). In a first step, we assign every worker who finds a new job in a given year *randomly* to one of the job openings that is being filled in that specific year. We then calculate the share of workers who under this random allocation would be observed working with at least one of their former coworkers, and relate this random exposure to former coworkers to the real exposure measured in the data. As shown in column (1) of Table 2, while over the period 1991 to 2005 the observed share of workers who start a new job in a establishment with at least one former coworker present is 33.33 percent, the corresponding "random exposure" to former coworkers amounts to only 2.11 percent. The ratio of these two numbers of 15.80 provides a summary measure of

[14]Rather than dropping the workers subject to these restrictions from the sample, we assign them to the group of workers who were hired already prior to 1991, making this group essential a "residual" group with wage and turnover patterns that have no clear economic interpretation.

Table 2: Overexposure Index, 1991-2004

	Conditioning Variables				
	Unconditional	Region	Region Gender Education	Region Gender Education Industry	Region Gender Education Industry Occupation
	(1)	(2)	(3)	(4)	(5)
Observed Exposure	33.33	33.33	33.33	33.33	33.33
Random Exposure	2.11	9.48	11.40	18.33	23.31
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Overexposure Index	**15.80**	**3.52**	**2.92**	**1.82**	**1.43**
	(0.05)	(0.01)	(0.00)	(0.00)	(0.00)

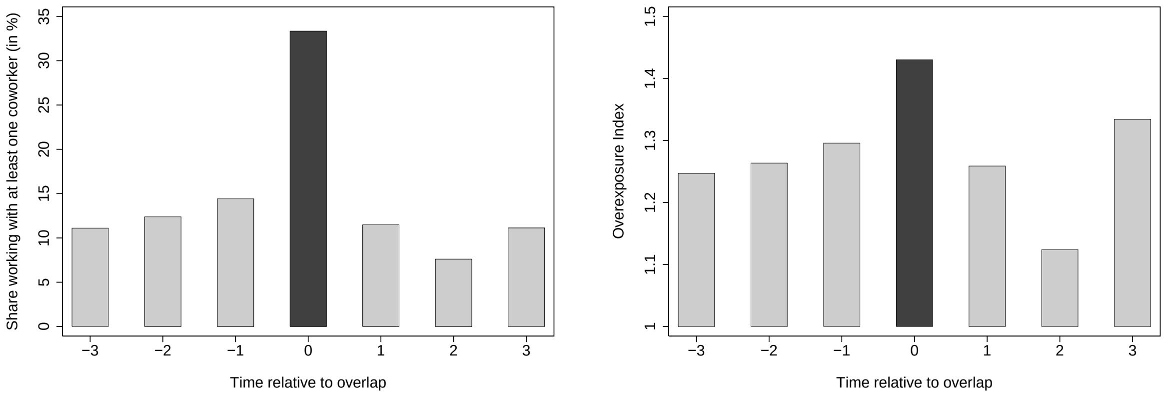
Note: The table reports the observed share of workers working with at least one of their former coworkers ("observed exposure"), the shares observed after randomly allocating workers to jobs ("random exposure"), and the ratios of the two together with their standard deviations. Random exposure measures are based on 10 simulations of the allocation process. Conditioning variables are 271 regional labor markets, gender, three education groups (some high school, high school/vocational training, and college education), 16 distinct industries, and 90 occupation groups.

the degree of *overexposure* to former coworkers (see Åslund and Skans, 2010, for a similar approach).[15]

It is clear that a completely random allocation of workers to all types of job openings across the whole of Denmark is not a reasonable counterfactual of worker mobility in the absence of referrals. Workers typically look for openings in their own local labor markets and move into jobs with skill requirements that match their own characteristics. Since former coworkers are likely to look for jobs in the same local labor markets and often share a similar skill set, their likelihood of ending up once again working together at the same establishment is higher than what an unconditional random allocation of workers to jobs would suggest. To deal with this issue, we extend our random allocation procedure by allocating workers to jobs conditional on observable characteristics. For example, we randomly allocate men with low education levels who find a job in the region of Aarhus only to jobs that we observe being filled in the region of Aarhus by men with low education levels. The allocation process is thus carried out "within" skill group (in the example, conditional on region, gender and education). As shown in column (2) of Table 2, conditioning on the local labor market in which a worker searches for a new job increases the random exposure to former coworkers to 9.48 percent, and consequently decreases the overexposure index to 3.52. Columns (3)

[15] We report the average share of workers observed working with at least one former coworker obtained from 10 distinct random allocations of workers to jobs. Due to the large sample of job starters, the standard deviations of these 10 shares are extremely small.

Figure 3: Working with Real and Placebo Former Coworkers



Note: The left panel reports the share of movers who are observed working with at least one of their real former coworkers (time relative to overlap = 0) and with at least one of their placebo coworkers from different pre- and post-overlap time periods. The right panel reports the overexposure index for each group of placebo and real former coworkers, defined as the ratio of the observed share working with at least one coworker of the corresponding group and the share obtained after randomly allocating workers to jobs conditional on region, gender, education, industry and occupation.

to (5) report the overexposure index for an increasingly large set of conditioning variables. The more characteristics one conditions on, the larger is the share of workers who end up working with at least one former coworker under random allocation. After controlling for the region, gender, education, industry, and occupation in which a worker searches for a job, the random exposure reaches a share of 23.31 percent, implying an overexposure index of 1.43.

While the overexposure indices reported in Table 2 suggest that the observed propensity of working with at least one former coworker has a systematic component that is not the result of pure coincidence and observed skill similarity, there remains a concern that the conditioning variables available are too coarse to pick up all factors that drive coworker mobility patterns but are unrelated to referrals. Workers who used to work in the same establishment in the past are likely to share a set of very specific skills, either because these skills were required to get a job at that establishment or because they accumulated these skills while working there. This commonality in establishment-specific skills could be the reason for why workers tend to end up in establishment in which other former coworkers are already present. To test for the relevance of such establishment-specific skills in determining mobility patterns, we follow Hensvik and Skans (2016) and define for each worker in our sample the set of *placebo coworkers* as all those individuals who either left a worker's establishment in any of the three years prior to him joining that establishment or who entered a worker's establishment in any of the three years after he left that establishment. Placebo coworkers have thus worked at the same establishments as the workers in our mover sample but never personally interacted with them at the workplace. Any difference between the propensity of working with a real former coworker and working with a placebo former coworker is thus likely to be driven by the personal nature of the contact rather than differences in unobservable establishment-specific skills.

The left panel in Figure 3 shows that the share of workers of 33.33 percent who start a job in a establishment with at least one real former coworker present is substantially higher than the corresponding shares working with at least one placebo coworker from the two pre- and post-groups. For example, the share of workers who start working in a establishment with at least one placebo coworker who last worked in the same establishments as the worker in question three years before he joined that establishment is 11.11 percent. Similarly, the share of workers working with at least one placebo coworker who joined the same establishment three years after the worker had left the establishment is 11.12 percent.

While these figures suggest some fundamental difference between real and placebo coworkers in determining workers' mobility choices, they have to be interpreted with care since the number of real coworkers is, on average, much higher than the number of placebo coworkers in any of the six pre- and post-periods considered. Following the same argument as before, part of the higher propensity to work with real former coworkers could thus be due to chance and the fact that there are simply more potential real coworkers around with whom one could end up working. To address this issue, we rely again on the random allocation procedure and construct overexposure indices for each group of placebo coworkers, measured as the ratio of the observed share of workers working with at least one placebo coworker of a specific group and the corresponding share obtained after randomly allocating movers to job openings, conditional on region, gender, education, industry and occupation. As shown in the right panel of Figure 3, the resulting overexposure index with respect to real former coworkers is still significantly higher than the overexposure indices with respect to any other group of placebo coworkers, suggesting that the personal contact to real former coworkers plays an important role in determining in which establishments workers start their new jobs. Overall, the evidence in this section thus supports our assumption that, conditional on observable characteristics, observing a worker following a former coworker into the same establishment can serve as a valid proxy for having obtained the job through a referral.

6 Results

6.1 Main Results

Table 3 reports the main results from estimating equation (1), where the dependent variable is either log wages (columns (1) to (3)) or an indicator for whether the worker left the establishment by the end the next year (columns (4) to (6)). Our preferred specifications reported in columns (3) and (6), which include a full set of establishment fixed effects and controls quadratically for the accumulated occupational experience of a worker, show that starting a new job in an establishment with a former coworker present increases initial wages by around 4.4 percent and reduces the probability of leaving the establishment in the first period by 2.2 percentage points. The estimates on the interaction of the coworker indicator and tenure further indicate that the initial wage and turnover effects diminishes over time at a rate of 0.7 and 0.3 percentage points, respectively.

As the results from the previous section suggest, not all the effects arising from starting a job in an establishment with a former coworker present necessarily reflect the impact of a

Table 3: Wage and Turnover Effects

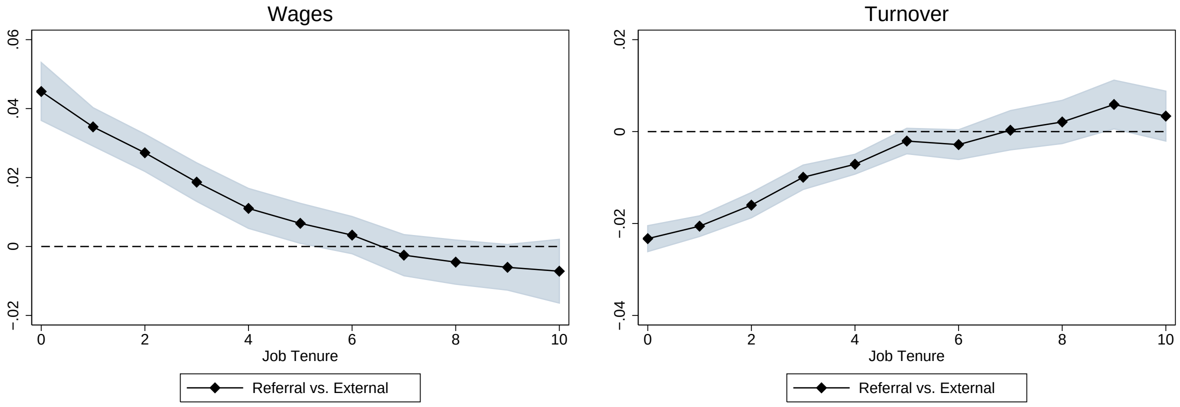
	Wages			Turnover		
	(1)	(2)	(3)	(4)	(5)	(6)
Coworker Present	0.044**	0.046**	0.044**	-0.040**	-0.024**	-0.022**
	(0.005)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Coworker × Tenure	-0.008**	-0.007**	-0.007**	0.008**	0.004**	0.003**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Establishment FE		✓	✓		✓	✓
Occupational Exp.			✓			✓
R-squared	0.275	0.441	0.442	0.100	0.181	0.182

Note: All estimations based on 22,538,034 observations in the period 1991 to 2004. Additional regressors included are tenure, tenure squared, age, age squared, accumulated experience, experience squared, log establishment size, year dummies, industry dummies, education group dummies, a gender dummy, a dummy for being an immigrant, and a dummy for having been hired before 1991. All dummies are interacted with tenure and tenure squared. Standard errors are clustered at the regional labor market level. A * and ** indicate statistical significance at the 5 and 1 percent level.

referral. The results from column (5) of Table 2, for example, imply that 69.9 percent of the observed propensity to work with a former coworker can be explained by workers sorting into establishments based on observable characteristics. If that type of sorting was indeed unrelated to the use of referrals, we would need to scale our parameter estimates by multiplying them by a factor of 3.3 (1/(1-0.699)) to obtain an estimate of the effect of referrals on wages and turnover. However, since part of the observed sorting based on observable characteristics may be the result of referrals, the appropriate scaling factor is likely to be smaller than that. In what follows, we will therefore continue to interpret our parameter estimates as directly reflecting the effect of referrals, with the implicit understanding that they are likely to constitute a lower bound of the true impact of coworker referrals on labor market outcomes.

While the parametric results in Table 3 conform to the central predictions of our theoretical framework, the econometric specification is not sufficiently flexible to capture its more subtle implications. In particular, the model predicts convergence in wages and turnover probabilities between workers hired through a referral and workers hired in the external market, where the long-run differences are necessarily zero for turnover, but depend on the differences in average skills and match-specific uncertainty in the two markets for wages (see Section 2). A linear interaction term is unsuitable for testing these predictions as it necessarily predicts a cross-over of the corresponding profiles at some level of tenure. To address this issue, we extend our baseline specification in equation (1) by replacing the main and quadratic tenure regressors and their interactions with the coworker indicator by a full set

Figure 4: Convergence Profiles



Note: Reported coefficients taken from a single regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile.

of tenure dummies, thus effectively estimating the wage and turnover convergence profiles non-parametrically.[16] In addition, we also allow for fully flexible age, labor market experience and occupational experience profiles, the other three control variables that are likely to pick up life cycle patterns of earnings and job mobility and are potentially correlated with the size of a worker's network and hence the propensity to start working in a job with a former coworker already present.

Figure 4 plots the estimated coefficients of the interaction terms which capture the evolution of the differences in log wages and turnover between workers who obtained their job through a referral and workers who obtained their jobs through the external market. According to these estimates, referred workers earn 4.6 percent higher wages in the first period after being hired than workers who obtained their jobs through the external market. This initial wage advantage declines steadily and at a decreasing rate with the duration of the employment spell, reaching zero after around six years of tenure. After that there is a further slight reduction in the relative wages of referred workers, to -0.7 percent after ten years of tenure although this difference is not statistically significant at conventional levels. For turnover, we find the reverse pattern. Initially, referred workers are 2.3 percentage points less likely to leave their employer than workers hired through the external market (which corresponds to 5.4 percent relative to a baseline turnover probability in the first year of a worker's employment spell of 42.6 percent). As predicted if employers learn about the match-specific productivity of their workers over time, this difference declines over time, reaching zero after five years of tenure and remaining there for subsequent periods of the employment spell.

The convergence profiles in Figure 4 thus strongly support the key predictions of our theoretical framework. The finding that, in the long run, wages of referred workers seem to be lower than those of external hires (see also Brown et al., 2016, for a similar finding) could

[16]Note that we also interact the indicator variable for the residual group with the full set of tenure dummies.

indicate a lower average skill level among workers who rely on informal contacts to find their jobs (see Section 2). Note, however, that differences in average match-specific productivity are not a necessary condition for the observed long-run difference in relative wages, since differences in match-specific uncertainty alone could already give rise to a corresponding pattern due to the particular selection of workers hired through the external market. In order to separate these two explanations for the long-run difference in wages, we will need to estimate the full model. This is done in Section 7 where we will return to this particular point.

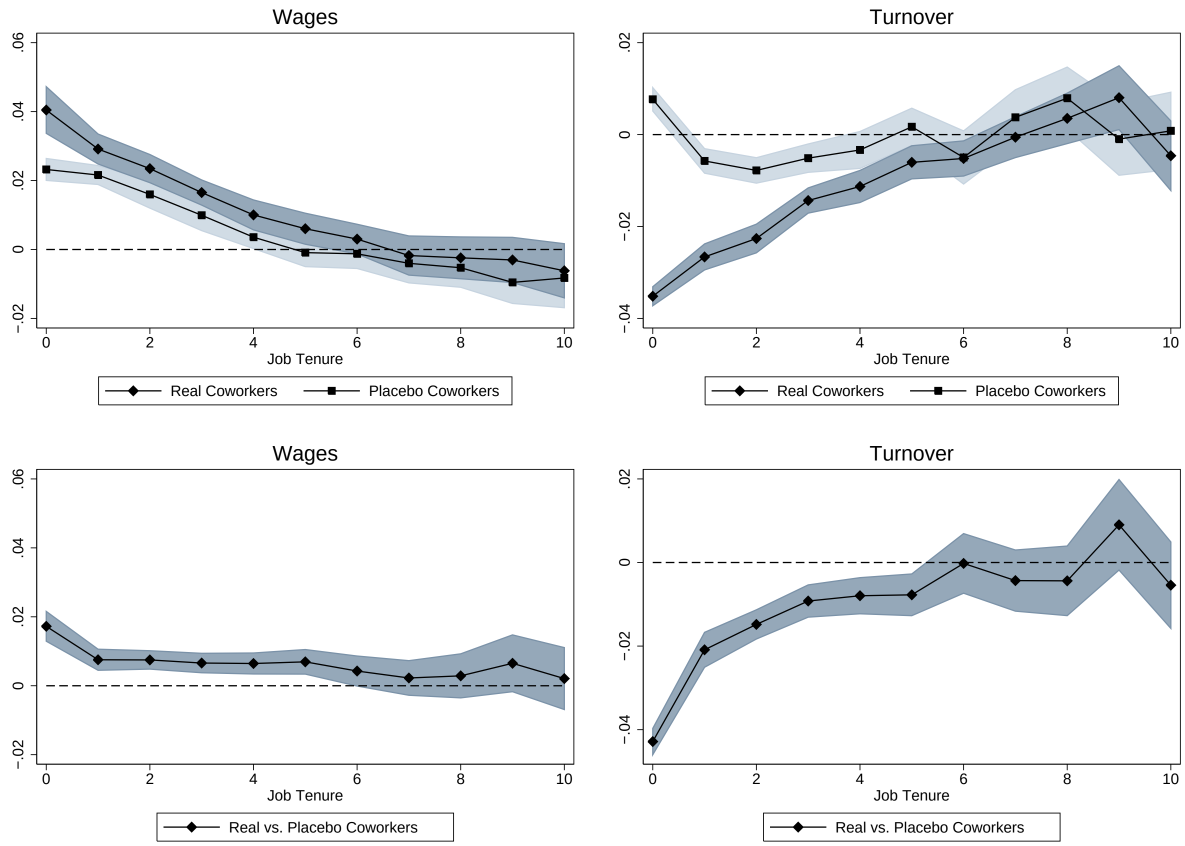
6.2 Placebo Coworkers

A potential alternative explanation for why workers earn higher wages when starting their job in an establishment with a former coworker already present could be productivity spillovers. Because workers used to work together in the same establishment in the past, they are likely to share certain unobservable skills that could lead to complementarities also at their new establishment. To test for the importance of this alternative mechanism, we distinguish in our estimation between jobs that are started in establishments with at least one real former coworker present and jobs in establishments with at least one placebo (but no real) former coworker present, where placebo coworkers are defined as in Section 4.

The upper panels of Figure 5 show the corresponding convergence profiles. For wages, we see that the presence of both real and placebo coworkers leads to higher starting wages and subsequent convergence relative to workers hired externally. The impact on initial wages, however, is significantly more pronounced for those workers who start their job in establishments with a real former coworker present. According to the lower left panel, which displays the corresponding differences between the two convergence profiles in the upper panel together with the respective confidence intervals, workers starting their job in establishments with a real former coworker present earn 1.7 percent higher wages in their first year than workers starting in an establishment with only a placebo coworker present. As predicted in the presence of learning about match-specific productivity, this difference declines over time and becomes close to zero after six years of tenure.

While real and placebo coworkers should share similar skills with the focal worker, only real former coworkers had the chance to personally interact with the focal worker in question in the workplace, which is typically a prerequisite for a subsequent job referral. The estimates in the lower panel of Figure 5 can thus be interpreted as the effect of obtaining a job through a referral net of any potential productivity spillovers arising from complementary skills. However, since joining an establishment with a placebo coworker present could still be the result of a referral, for example because of indirect linkages between the placebo coworker and the focal worker in question, we refrain from calling only the differential effects between real and placebo coworkers a "referral effect". Without further information, it could just as well be that both profiles represent the effect of referrals on labor market outcomes, with the effects of referrals from placebo coworkers somewhat muted, because their link to the

Figure 5: Convergence Profiles - Placebo Coworkers



Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile. The top panels show the relative wage and turnover profiles, the bottom panels the difference between these profiles at any value of job tenure.

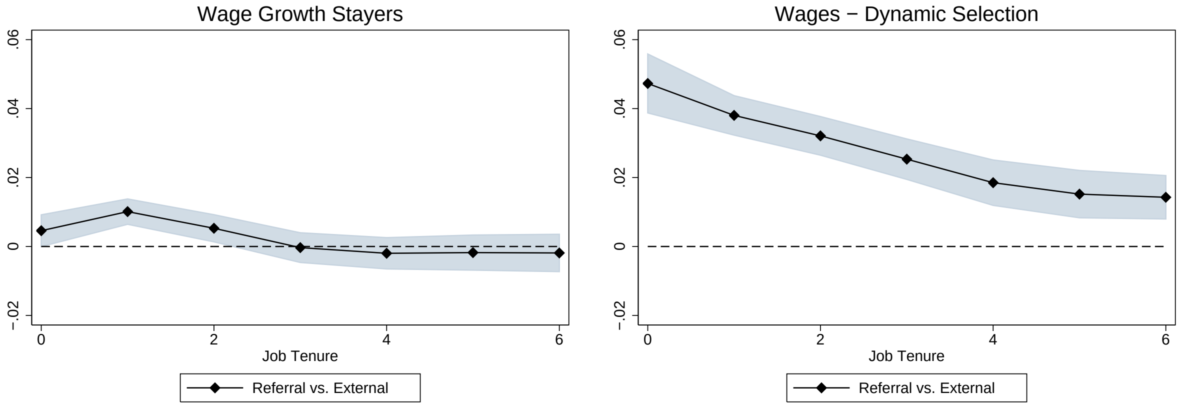
worker in question is weaker and thus the information provided less precise.

Regarding the effect on turnover, there is a pronounced difference between workers who start their job in an establishment with a real former coworker present and workers who start their job in an establishment with just a placebo coworker present. Only the presence of a real coworker leads to a noticeable reduction in the initial job turnover probability and subsequent convergence over time. The effect associated with the presence of placebo coworkers, in contrast, is positive and very small in the first period, albeit still statistically significant due to the large sample size, and hovers around zero in the periods thereafter. Within our theoretical framework, this pattern is not fully consistent with the muted, but still discernible wage convergence profile, indicating that the wage impacts associated with the presence of a placebo coworker may not be driven exclusively by some kind of indirect and therefore less accurate referral.

6.3 Differential Wage Growth vs. Dynamic Selection

The key prediction of the theoretical model that wages of workers hired through the referral and the external market should converge over time is the result of two distinct mechanisms. First, through learning about the true match-specific productivity of workers, employers

Figure 6: Individual Wage Growth vs. Dynamic Selection



Note: Reported coefficients taken from a single regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimates in the left panel are the differences in wages between workers with a referral job and workers with an external job conditional on both groups spending more than six years at the hiring establishment. The estimates in the right panel are the differences in wages between workers with a referral job and workers without a referral job conditional on both groups leaving the hiring establishment within the first six years. The estimation sample excludes movers with a network size beyond the 99th percentile.

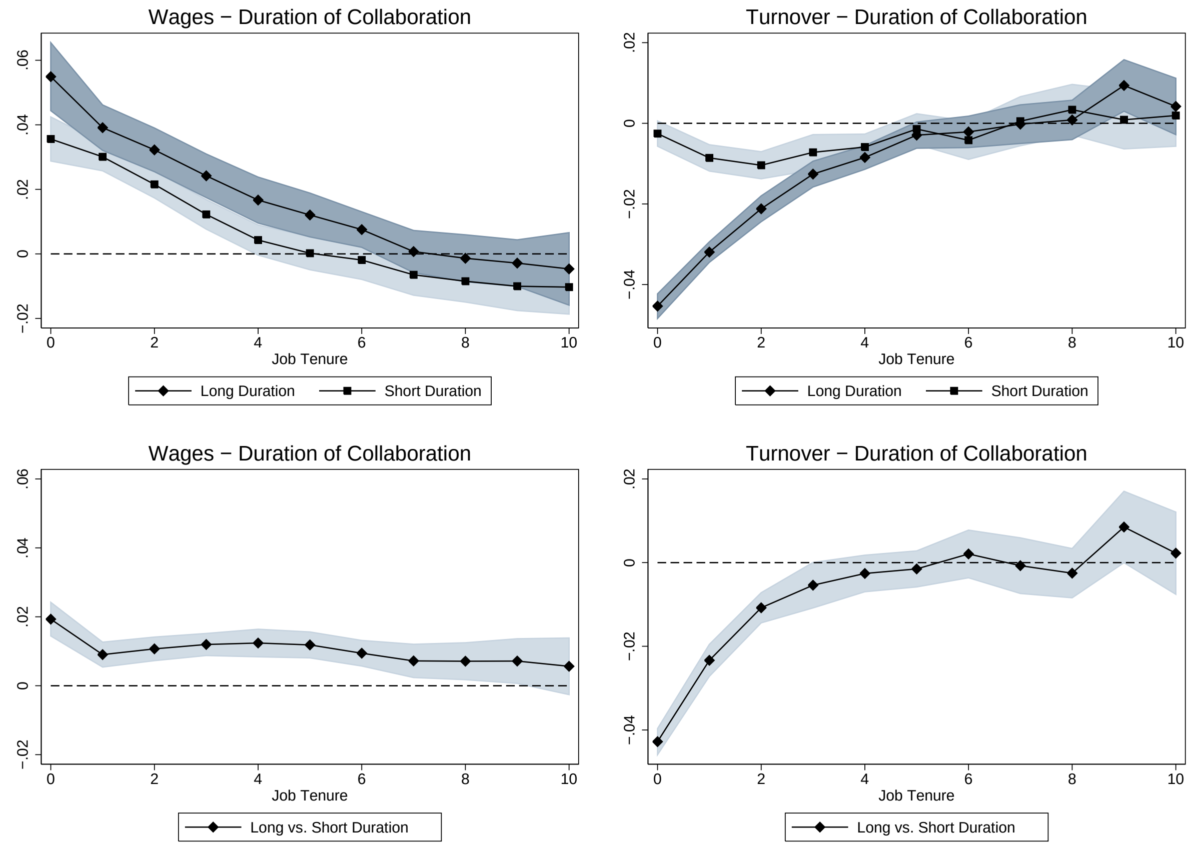
are gradually able to identify and separate from poor matches, keeping only those workers with match-specific productivity above the reservation match quality. Due to the higher degree of initial uncertainty, this dynamic selection process is stronger among workers hired through the external market. As a result, the composition of workers remaining at a given establishment changes at a faster rate towards workers with high match quality in the group hired through the external market than in the group hired through referrals, generating convergence in observed average wages. Second, for a given worker, wage growth is less pronounced if he was hired through the referral market since, due to the higher precision in the initial signal, the expected match productivity at the beginning of the employment relationship is already closer to the true match-specific productivity that is eventually revealed through learning.

To investigate the relative importance of these two sources of wage convergence, we estimate wage profiles separately for workers who stay in the hiring establishment for more than six years ("stayers") and workers who separate from the establishment within the first six years. We choose six years since, according to Figure 4, this is the time by which learning is essentially completed. As shown in Figure 6, both mechanisms, within worker wage growth (labelled Wage Growth Stayers) and dynamic selection (labelled Wages - Dynamic Selection), contribute to the observed wage convergence. However, the dominant force is clearly the dynamic selection mechanism, suggesting that average wages converge primarily because of a more extensive weeding-out of bad matches among externally hired workers.

6.4 Intensity of Contact

The extent to which referrals can reduce the uncertainty about match-specific productivity between workers and establishments should depend on the quality of the information the

Figure 7: Convergence Profiles - Duration of Collaboration



Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile. Long durations correspond to more than 1.5 years of collaboration, short durations correspond to up to 1.5 years of collaboration. The bottom two panels show the difference in the profiles depicted in the respective upper two panels together with their 95% confidence intervals.

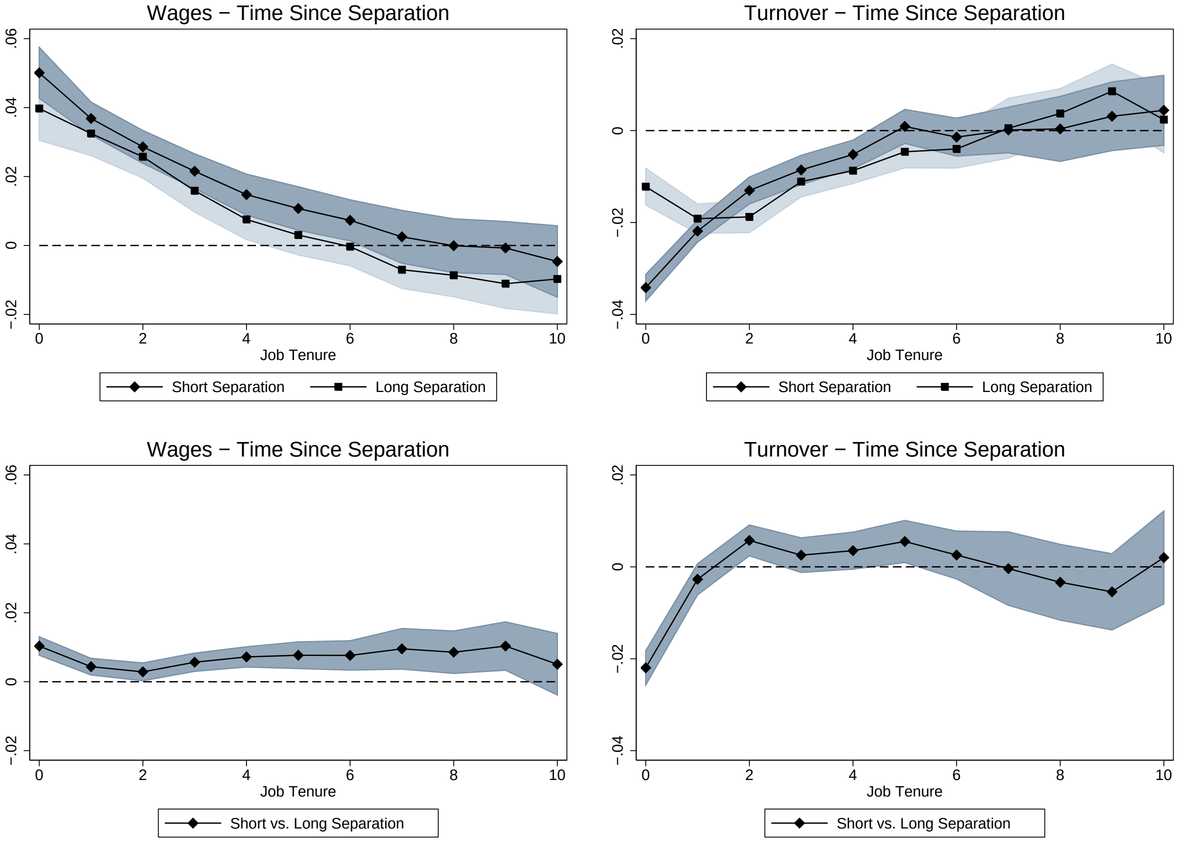
referral provider is able to pass on to his employer when making the referral. This quality, in turn, is presumably a function of the past intensity of interaction between the focal worker and the coworker who makes the referral since more interaction should allow workers to better observe the idiosyncratic skills of their coworkers and assess their suitability for a potential job opening.

To test this hypothesis, we use two standard proxies for the intensity of prior interaction: the duration of past collaboration and the time that has passed since separating from each other. For both these proxies, we compute the median value in our sample of focal workers, which is one year for the duration of collaboration and four years for the time since separation, and then distinguish between the two groups of former coworkers above and below the median.[17]

Figure 7 shows the wage and turnover profiles for worker-coworker pairs who spent a long time working together and those who spent relatively little time working together. Consistent with the theoretical predictions, the effects on the initial wage and turnover probability is significantly larger for workers who join a former coworker with whom they

[17] If there are more than one former coworker present in the new establishment, we use the average value of the duration of collaboration and the time passed since separation to identify a high or low intensity link.

Figure 8: Convergence Profiles - Years Since Separation

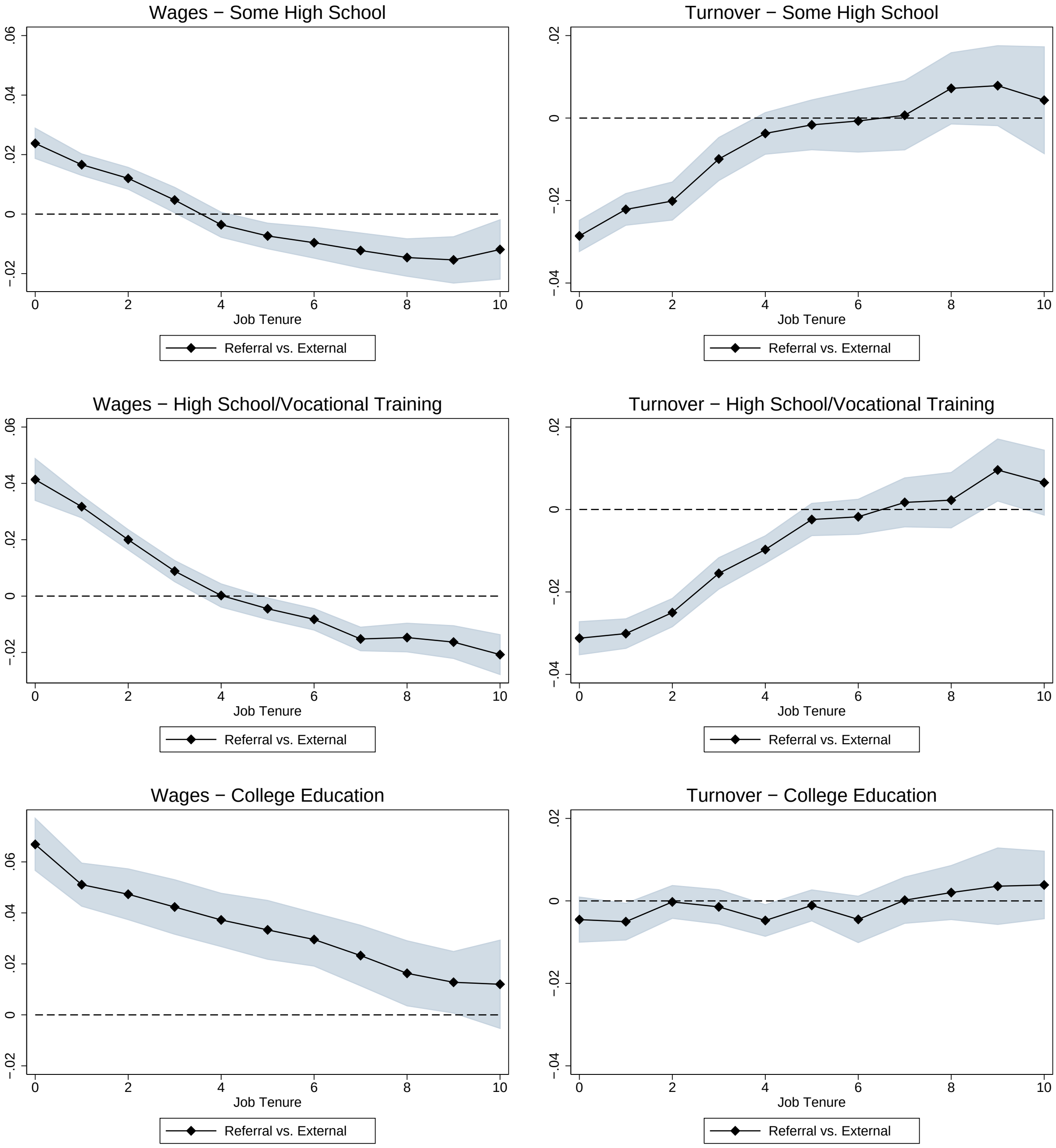


Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile. A short separation took place at most four years ago, a long separation took place more than four years ago. The bottom two panels show the difference in the profiles depicted in the respective upper two panels together with their 95% confidence intervals.

spent at least two years working together (note that in our data, durations of collaboration can only be measured at discrete annual intervals). The difference in initial wages is about 2 percent and declines only slowly over the first 10 years in the establishment. Having spent more time together working in the same workplace thus seems to enable the coworker who provides the referral to pass on more accurate information to their employers.

Corroborating the reinforcing role of a higher intensity in the worker-coworker relationship for subsequent labor market outcomes, Figure 8 shows that referrals from coworkers with whom the focal worker used to work until relatively recently have a significantly larger effect on initial wages and turnover probabilities than referrals of coworkers from whom the focal worker separated a long time ago. This finding is consistent with a declining ability of workers to provide accurate information about their former coworkers in the absence of any ongoing interaction in the workplace. Together, Figures 7 and 8 demonstrate that the intensity of the connection between workers plays an important role in the referral process.

Figure 9: Convergence Profiles - Education Groups



Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile.

6.5 Heterogeneity

In this section, we study the heterogeneity of the role of referrals for labor market outcomes across different socioeconomic subgroups. The theoretical model predicts that the effect of a referral on initial wages and job stability should be particularly strong among groups of workers for which, a priori, there is more uncertainty and less information available on which employers could base their hiring decision.

Figure 9 shows separate results for workers with three different levels of education: workers with some high school education, workers with completed high school education or vocational training, and workers with college education. The general pattern of higher initial wages and lower job turnover probability is visible in all three education groups. However, in terms of wages and contrary to the findings by Brown et al. (2016), referrals seem to play a more important role the higher the level of education. The initial wage gain from being hired through a referral amounts to around 2.4 percent for low-skilled workers, 4.2 percent for medium-skilled workers, and 6.9 percent for high-skilled workers. In terms of turnover, however, we find the opposite with referrals having the smallest impact for high-skilled workers.

As discussed in Section 2, the finding that for low- and medium-skilled workers the long-run wage gap is negative and significantly different from zero indicates that either average match quality ($\overline{y}_R$) or match-specific uncertainty (σ_R) or both are lower in the referral market than in the external market. Our structural estimates (see Section 7) show that it is in fact the lower amount of noise in the referral market that is driving these long-run differences in wages for these types of workers whereas average match quality is found to be higher in the referral than the external market. For high-skilled workers, we find that the wage difference remains positive even in the long run, suggesting that in this market referrals enable firms to access a more productive pool of workers.

Figure C-1 in the appendix shows the corresponding results for different age groups. Because of their shorter cv, young workers have arguably more to gain from using referrals. However, this is not confirmed by the empirical results which show similar initial wage gains for all three age groups from being hired through a referral. Figures C-2 and C-3 show additional results separately for men and women and immigrants and natives. The results for these groups are generally quite similar, with slightly larger wage effects for men and immigrants and smaller turnover effects for immigrants than natives.

7 Model Estimation

In this section, we estimate the structural parameters of the model presented in Section 2, using the reduced-form results presented in the previous section as auxiliary parameters to fit. There are two main objectives of this exercise. The first is to show that our main findings about convergence in wage rates and turnover can be reconciled with the theoretical model. Knowledge of the underlying structural parameters then allows us to explore the mechanisms that generate the reduced-form results in more detail and assess their relative importance. The second objective is to perform counterfactual simulations to assess the overall importance of the referral market. We estimate the model by indirect inference, setting the unit of time to one year in line with the nature of our administrative data. Wages are log hourly wages and tenure is measured discretely in years as in the data. The model is simulated in steady-state with 105 million workers.[18] The details on how we implement

[18]The reason for simulating this many workers is that the probability of observing wages and turnover rates after 10 years, statistics that we want to fit, is small given that our data window is only 14 years. Thus, we need a lot of workers to avoid large simulation errors.

the simulation can be found in Appendix A.5.

7.1 Auxiliary Parameters

To estimate the model, we choose a number of auxiliary parameters that we want to match. Most importantly, these are the differences in wages and turnover probabilities at different values of tenure depicted in Figure 4. In terms of identification, there is a relatively close mapping between specific sources of identifying variation in the data and individual model parameters. The initial differences in wages and turnover are primarily informative about both the relative average match qualities in the referral and external market, $\overline{y}_R$ and $\overline{y}_E$, and the differences in the market-specific noise terms, σ_R and σ_E (compare Figure 2). The higher the average match quality and the lower the noise in the referral market relative to the external market, the higher the initial wage and turnover gap. To separately identify the role of relative average match productivity and relative uncertainty, the long-run difference in wages provides identifying variation since it is primarily driven by differences in productivity. The evolution of the differences in wages and turnover probabilities as tenure increases, in particular the speed of convergence, is the main source of identification for the learning parameter α. However, the shape of these convergence profiles also contributes to the identification of σ_R and σ_E.

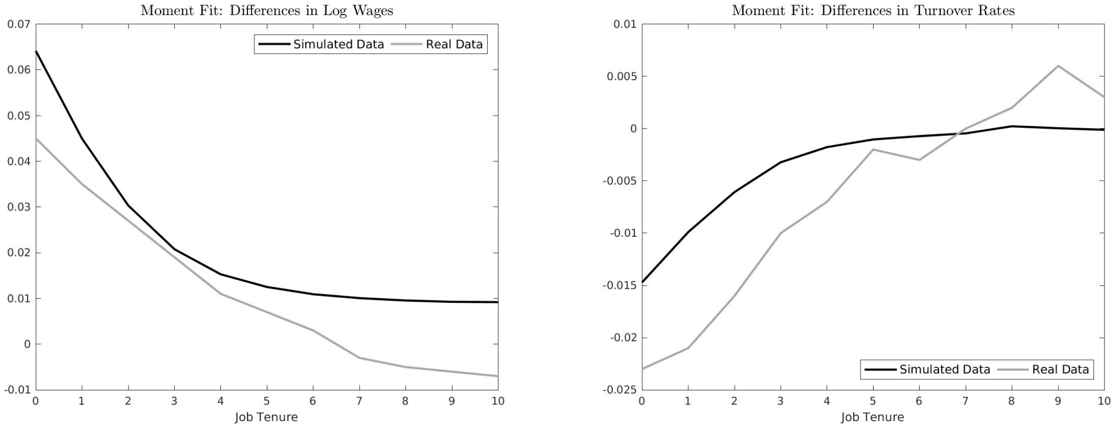
In addition to the wage and turnover convergence profiles, we also match on tenure-specific average wages and turnover probabilities in the external market. This is in order to match the levels of these moments and not just the difference. Matching the levels, especially those of the turnover probabilities, also helps to identify δ since this is the only source of job displacement at high values of tenure in the model. We further match on the average wage across all workers, which identifies the level of average match qualities. Finally, even though the job offer arrival rates λ_R and λ_E are indirectly identified from the convergence profiles and the tenure-specific average wages and turnover probabilities in the external market, we also match on the probabilities of observing a worker unemployed at time t but working in market k at time $t+1$. This gives more direct information on the arrival rates of job offers. We set $r = 0.05$ and $b = 2.505$ which ensures that the income received while unemployed amounts to 50 percent of the average wage, reflecting the prevailing situation in Denmark. Appendix A.6 describes the full set of auxiliary parameters in the estimation and their computation from the simulated data.

7.2 Fit and Estimates

Table B-1 in the appendix reports the full set of real data moments and their corresponding simulated values. Given that we fit 47 auxiliary parameters using only 9 structural parameters, the model does a good though certainly not perfect job of matching the key empirical patterns. Figure 10 depicts the real and simulated relative wage and turnover profiles.

While the overall convergence patterns are clearly captured, the model struggles to fit the convexity of the relative wage profile and the concavity of the relative turnover profile in the

Figure 10: Auxiliary Parameter Fit



Note: Wage and turnover differences correspond to the estimates depicted in Figure 4. $\overline{w}_k(s)$ and $h_k(s)$ is the average wage and hazard rate for workers with tenure s hired through market k. $\overline{w}$ is the average wage. $PrUE_k$ is the probability of having a job in market k at time $t+1$ given the worker was unemployed at time t. The auxiliary parameters are described in full detail in Appendix A.6.

data. In particular, there is a tension in the model between the initial difference in turnover rates and the initial difference in log wages, with the turnover gap being more pronounced in the data, but the wage gap being larger in the estimated model. While a better match of the initial turnover gap could be achieved, for example, by a lower value of the learning parameter, α, or the noise term, σ_R, these changes would further increase the convexity of the simulated wage profiles and the mismatch in terms of initial wages (compare Figure 2). With many more auxiliary parameters than structural parameters, however, the fact that the model cannot perfectly match the data is not entirely surprising. In the next section, we report results from an alternative specification which, at the expense of a poorer fit for intermediate auxiliary parameters, does a better job in fitting the initial and final wage and turnover gaps.

Table 4 shows the structural parameter estimates from our main specification together with their standard errors. Not surprisingly, given the use of population-wide data, all parameters are very accurately estimated. We estimate σ_R to be 0.496 and σ_E to be 0.580, indicating that the standard deviation of the noise term is 14.5 percent lower in the referral market than in the external market. The parameter estimate for α of 0.662 implies that the true productivity of a worker is revealed after, on average, 1.51 years of employment, reflecting the relatively quick wage and turnover convergence we find in the data.[19] The finding that learning about match-specific productivity takes place within a few years is consistent with the broader evidence in the literature that employer learning on workers' unobserved productivity tends to be relatively fast (see e.g. Lange, 2007). The estimates of λ_E and λ_R show that job offer arrival rates are about four times higher in the external than

[19] In the discrete time model of Dustmann et al. (2016), the probability that true match-specific productivity is revealed in any given year is estimated to be 0.50 which is very close to the corresponding magnitude implied by our estimate of α (given by $1 - \exp(-\alpha) = 0.484$). In contrast, they estimate that the standard deviation of the noise in the referral market is 23.4 percent lower than in the external market, compared to our estimate of 14.5 percent. This more pronounced reduction in uncertainty could be due to the fact that Dustmann et al. (2016) focus on foreign citizens for whom uncertainty tends to be larger to start with and who therefore have more to gain from a referral.

Table 4: Estimates and Standard Errors

	Estimate	Std. Err.
σ_R	0.496	0.011
σ_E	0.580	0.006
σ_Y	1.330	0.007
λ^E	4.834	0.054
λ^R	1.137	0.005
δ	0.197	0.002
α	0.662	0.031
$\overline{y}_R$	2.967	0.007
$\overline{y}_E$	2.836	0.004

Note: We estimate the model using 105 million workers. Standard errors are computed using the formula in Gourieroux et al. (1993), which is the standard formula for standard errors in this type of structural models. We use a step-size of 10^{-3} but have done robustness checks with several different step-sizes and the results do not change. The weighting matrix is an identity matrix, so each auxiliary parameter gets the same weight.

in the referral market. The average match-specific productivity of workers in the referral market $\overline{y}_R$ is 14.0 percent higher than in the external market, indicating that referred workers are drawn from a pool of relatively productive workers.[20,21]

Given the estimates of the distributional parameters, we are able to compute the two reservation expected match qualities m_R^* (4.168) and m_E^* (4.133) and the probability of accepting a job offer conditional on matching, which is 16.7 percent in the referral market and 14.7 percent in the external market. Thus, while job offers arrive at a higher rate in the external market, they are more likely to be accepted in the referral market, in line with the findings by e.g. Galenianos (2013), Burks et al. (2015) or Brown et al. (2016).

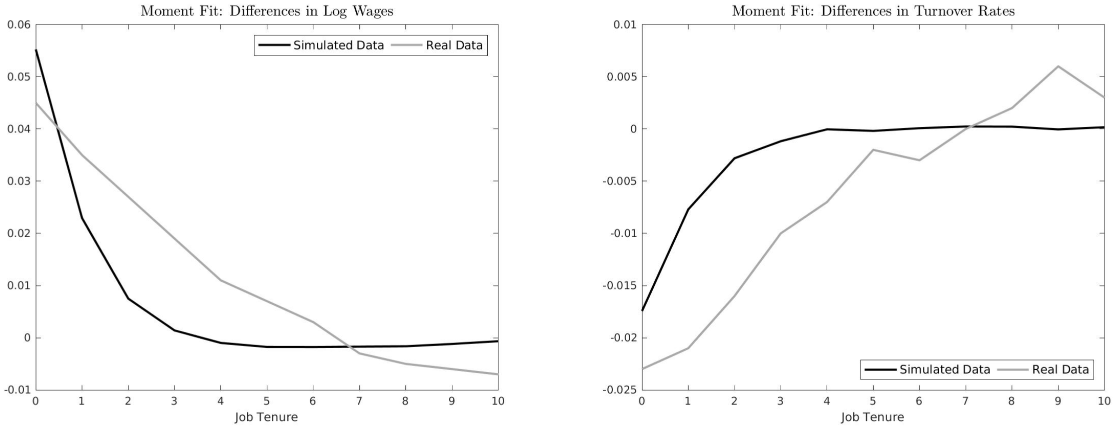
7.3 Alternative Weighting Matrix

In our baseline estimation, we are unable to match the wage difference at high values of tenure (see the left panel of Figure 10). As pointed out in the discussion of our auxiliary parameters, we believe this to drive the large difference in the estimated average match productivities. In this section, we show that our main qualitative conclusions are not driven by this particular shortcoming of our model. We do this by estimating an alternative model with different weights compared to the baseline model (in which we assign equal weights to all auxiliary parameters). In this model, we put a weight of zero on all differences in wages and turnover rates *except* at the lowest and highest values of tenure, which we each give a weight of 100. We do the same for the levels of turnover and wages but here only

[20]We view this as an upper bound driven by the models inability to fit the difference in wages at high tenure levels. We return to this point in the next section, where we estimate an alternative model.

[21]Note, that the auxiliary parameters are measured in log wages, so match productivities are really log productivities and thus the difference in the means of the distribution is approximately the percentage difference. We calculate the percentage difference as $e^{(\overline{y}_R-\overline{y}_E)}-1$.

Figure 11: Moment Fit: Alternative Model



Note: Wage and turnover differences correspond to the estimates depicted in Figure 4. $\overline{w}_k(s)$ and $h_k(s)$ is the average wage and hazard rate for workers with tenure s hired through market k. $\overline{w}$ is the average wage. $PrUE_k$ is the probability of having a job in market k at time $t+1$ given the worker was unemployed at time t. The auxiliary parameters are described in full detail in Appendix A.6.

give a weight of one to the moments at the lowest and highest values of tenure. Finally, we also assign a weight of one to the three remaining auxiliary parameters (the average wage and the two job finding probabilities). The primary goal of this estimation is thus to fit the degree of convergence in wages and turnover rates and not the entire profiles. The full fit of the auxiliary parameters together with the weights is reported in Table B-2 in the appendix. We show the convergence plots of wages and turnover rates in Figure 11. With the alternative weighting scheme, we now fit the long-run differences in wages and turnover rates a lot better. We also match the other auxiliary parameters with low weight reasonably well but miss out on the intermediate values of tenure, as expected since we did not put any weight on these.

In Table 5, we present the corresponding structural parameters. In the first two columns we report our baseline estimates from Table 4 for ease of comparison together with their standard errors. There are two major differences between the alternative model and our baseline model. First, the estimate of the speed of learning parameter α increases substantially, from 0.662 (implying a probability that true match-specific productivity is revealed in any given year of 0.484) to 1.045 (implied annual probability of 0.648). While this contributes to a better match with the initial and long-run differentials, the more pronounced convexity of the relative wage profile due to a higher α leads to a worse fit of the wage differentials at intermediate values of tenure. Second, the difference in average productivity, $\overline{y}_R$ versus $\overline{y}_E$, decreases, from 14.0 percent (baseline model) to 7.6 percent. This happens because a large difference in average productivity generally implies a large difference at high tenure levels, which is not what we observe in the data (see Figure 10 for the baseline model).

Based on these findings, we argue that the two models we propose capture different features of the data well. The speed of learning α and the noise terms σ_R and σ_E are most reliably estimated in the baseline estimation. The estimate of 14.0 percent for the difference in average match productivities in this model, however, constitutes an upper bound, with our preferred estimate of 7.6 percent coming from the alternative model.

Table 5: Estimates and Standard Errors: Alternative Model

	Baseline Model		Alternative Model	
	Estimate	Std. Err.	Estimate	Std. Err.
σ_R	0.496	0.011	0.386	0.008
σ_E	0.580	0.006	0.487	0.007
σ_Y	1.330	0.007	1.706	0.011
λ^E	4.834	0.054	3.871	0.061
λ^R	1.137	0.005	0.834	0.023
δ	0.197	0.002	0.260	0.033
α	0.662	0.031	1.045	0.018
$\overline{y}_R$	2.967	0.007	2.378	0.009
$\overline{y}_E$	2.836	0.004	2.305	0.005

Note: We estimate the models using 105 million workers. Standard errors are computed using the formula in Gourieroux et al. (1993), which is the standard formula for standard errors in this type of structural models. We use a step-size of 10^{-3} but have done robustness checks with several different step-sizes and the results do not change. The weighting matrix for the baseline model is an identity matrix and for the alternative model it is shown in Table B-2 in the appendix.

7.4 Heterogeneity

In this section, we present structural parameters estimated separately for different socioeconomic subgroups of the population, distinguishing by education, gender, age and ethnicity. As before, we match on the respective wage and turnover convergence profiles (depicted in Figures 9, C-1, C-2 and C-3), the wage and turnover levels in the external market, the average wage, and the probabilities of observing a worker unemployed at time t but working in market k at time $t+1$. The parameter estimates and standard errors are presented in Table 6.[22]

Focusing on σ_E first, the results indicate that match-specific uncertainty is most pronounced for highly educated workers (0.612), young workers aged 25 to 30 (0.752) and immigrants (0.670), all groups characterised by either relatively complex skill sets (highly educated workers) or shorter employment histories based on which employers could assess match-specific productivities (young workers and immigrants). We do not find any quantitatively important difference between men (0.583) and women (0.591).

A central finding across all groups is the lower degree of uncertainty in the referral market relative to the external market, suggesting that referrals transmit valuable information about all types of workers. In relative terms, the effectiveness of referrals in reducing match-specific uncertainty is most pronounced for low- and medium-educated workers and native Danes. The lower effectiveness of referrals for high-skilled workers could be due to the more complex nature of their skill sets whereas the lower information content of referrals for immigrants could be due to the fact that immigrants tend to be referred by other immigrants (see e.g.

[22]The fit of the auxiliary parameters is qualitatively similar to the full sample. The results are available upon request.

Table 6: Heterogeneity

	Education Groups						Gender			
	Low		Medium		High		Men		Women	
	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err
σ_R	0.470	0.001	0.458	0.000	0.579	0.001	0.498	0.000	0.504	0.000
σ_E	0.558	0.000	0.594	0.000	0.612	0.001	0.583	0.001	0.591	0.002
σ_Y	1.375	0.002	1.285	0.002	1.037	0.001	1.401	0.005	1.311	0.004
λ_E	2.959	0.005	3.179	0.002	4.703	0.004	3.710	0.003	4.783	0.008
λ_R	0.891	0.001	0.725	0.001	0.709	0.002	0.809	0.002	1.047	0.003
δ	0.220	0.001	0.207	0.001	0.177	0.000	0.198	0.001	0.195	0.001
α	0.803	0.003	0.644	0.003	0.507	0.012	0.683	0.001	0.661	0.005
$\overline{y}_R$	2.954	0.001	3.222	0.001	3.842	0.002	3.058	0.001	2.892	0.002
$\overline{y}_E$	2.908	0.000	3.194	0.000	3.625	0.000	2.927	0.000	2.811	0.001
	Age Groups						Immigrant Status			
	Young (25-30)		Middle (31-45)		Old (46-54)		Danes		Immigrants	
	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err
σ_R	0.649	0.000	0.438	0.001	0.368	0.001	0.469	0.000	0.612	0.001
σ_E	0.752	0.001	0.512	0.000	0.430	0.000	0.566	0.000	0.670	0.001
σ_Y	1.283	0.002	1.060	0.002	1.485	0.004	1.396	0.003	1.761	0.004
λ_E	4.686	0.003	3.757	0.007	4.979	0.009	4.356	0.003	3.473	0.004
λ_R	1.008	0.001	1.063	0.002	1.051	0.002	0.945	0.001	0.847	0.001
δ	0.239	0.000	0.180	0.002	0.175	0.001	0.203	0.001	0.229	0.001
α	0.599	0.008	0.644	0.011	0.670	0.006	0.653	0.006	0.745	0.003
$\overline{y}_R$	3.163	0.000	3.645	0.001	2.563	0.002	2.883	0.001	2.276	0.002
$\overline{y}_E$	3.080	0.000	3.509	0.000	2.324	0.001	2.777	0.000	2.099	0.000

Note: We estimate the models using 5 million workers. Standard errors are computed using the formula in Gourieroux et al. (1993), which is the standard formula for standard errors in this type of structural models. We use a step-size of 10^{-3}, but have done robustness checks with several different step-sizes and the results do not change.

McPherson et al., 2001, Glitz, 2014) and that employers potentially discount the information provided through such referrals.

For all socioeconomic groups, we find that $\overline{y}_R > \overline{y}_E$. The difference is especially large for highly-educated workers and older workers which explains the substantial positive long-run wage differentials depicted in Figures 9 and C-1. One hypothesis is that, for these particular groups, previous coworkers have more information available on which they can base their referral, allowing them to more successfully restrict the sample of referred workers to those especially suited for the job at hand. We also find a substantial difference in average match-specific productivity by ethnicity, with immigrants displaying a much larger difference between $\overline{y}_R$ and $\overline{y}_E$ than native Danes. This could be due to the significantly larger degree of uncertainty (σ_E) and baseline variability (σ_Y) in immigrants' skills, and their on average lower productivity compared to natives ($\overline{y}_E$). In such a context, referrals might be particularly effective in identifying more suitable workers for a given job.

Turning to the parameter α, the estimates suggest that employers learn fastest about the true match-specific productivity of low-educated workers (0.803, implying a probability that true match-specific productivity is revealed in any given year of 0.552) and immigrants (0.745, implied annual probability of 0.525) and slowest about highly-educated workers (0.507, implied annual probability of 0.398). This is expected since, due to the complexity and often team-based nature of high-skilled workers' jobs, employers have a harder time extracting relevant information about any particular worker when observing him on the job. As before, we do not find a big difference between the speed with which employers learn about the skills of men (0.683) and women (0.661). Finally, consistent with much of the existing evidence (Topa, 2011), our structural estimates show that the relative importance of the referral market in the job search process, as measured by the ratio of λ_R and λ_E, decreases with the education level of the worker.

7.5 Counterfactual Scenarios

One of the main advantages of having estimated a structural model is the ability to predict counterfactual scenarios. In this section, we quantify the contribution of the referral market to average wages, which in the model are equivalent to output, and average income, which comprises both wages and unemployment benefits. There are two mechanisms through which the referral market exerts a positive effect in our model. First, average match quality is higher in the referral market than in the external market, generating more productive matches even in the long run. Second, uncertainty in the referral market is lower, so that workers and firms find it easier to judge whether to form a match, leading to more productive matches already in the early phase of an employment relationship.

The first rows of Panels A and B in Table 7 show the distribution of workers across different labor market states in our baseline and alternative model respectively. Focusing initially on the baseline model, in steady-state the share of individuals who are employed with unknown productivity and were hired through the referral market (external market) is 5.1 percent (18.6 percent). 22.9 percent of individuals are unemployed and the remaining 53.4 percent employed with known productivity (e_2 in the model).[23] The average log wage is 4.997 and the average log income across all employed and unemployed individuals 4.425.

In the next three rows, we report the same outcomes for three counterfactual scenarios. In the first scenario, we isolate the role of the difference in uncertainty in the two markets by setting σ_R equal to σ_E. In the second scenario, we focus on the role of different average match productivities by setting $\overline{y}_R$ equal to $\overline{y}_E$. Finally, in the third scenario, we quantify the total effect of the referral market by setting both $\overline{y}_R = \overline{y}_E$ and $\sigma_R = \sigma_E$.

Comparing the outcomes in the first and last row of Panel A in Table 7, the results

[23]Note that unemployment in our data reflects non-employment since we do not condition on labor market attachment when selecting our sample. As a result, it comprises a significant fraction of individuals who are only marginally attached to the labor market.

Table 7: Counterfactual Market Structures

	e_R	e_E	u	Average Wage	Average Income
Panel A: Baseline Model					
Estimated Model	0.051	0.186	0.229	4.997	4.425
Model with $\sigma_R = \sigma_E$	0.052	0.187	0.229	4.990	4.420
Model with $\overline{y}_R = \overline{y}_E$	0.045	0.195	0.217	4.894	4.375
Model with $\overline{y}_R = \overline{y}_E$ and $\sigma_R = \sigma_E$	0.046	0.195	0.217	4.887	4.370
Panel B: Alternative Model					
Esimated Model	0.032	0.142	0.303	5.048	4.277
Model with $\sigma_R = \sigma_E$	0.033	0.142	0.303	5.044	4.274
Model with $\overline{y}_R = \overline{y}_E$	0.030	0.145	0.297	5.012	4.266
Model with $\overline{y}_R = \overline{y}_E$ and $\sigma_R = \sigma_E$	0.031	0.145	0.297	5.008	4.264

Note: e_R refers to the share of individuals employed with unknown productivity hired through the referral market, e_E refers to the share of individuals employed with unknown productivity hired through the external market, and u refers to the share of individuals in unemployment. The residual category e_2 refers to the share of individuals employed with known productivity.

show that the average wage in the economy would be 10.4 percent lower in the absence of a referral market.[24] This particular hiring channel thus contributes substantially to average wages (and output) in the economy. When equalizing only the noisiness of the signals in the two markets ($\sigma_R = \sigma_E$), the average wage decreases by a moderate 0.7 percent, indicating that most of the positive contribution of the referral market is driven by the difference in average match productivity.[25] Indeed, an equalization of average productivity in the referral and external market alone would decrease the average wage in the economy by 9.8 percent. This is because a decrease in the average match productivity in the referral market decreases both the number of workers hired through a referral e_R and the wage that these workers receive. For average income, which also depends on the fraction of individuals in unemployment, the patterns are similar.

In Panel B of Table 7, we present the same counterfactuals for the alternative model discussed in Section 7.3. Since in the baseline model, we were not able to match the wage differences at high values of tenure particularly well, we want to see whether this has implications for the estimated efficiency gains due to the existence of a referral market. Compared to the estimated wage decrease in the baseline model of 10.4 percent, the equalization of uncertainty and average match productivity in the referral and external market reduces wages by 3.9 percent, which is much smaller but still significant. We view this as a more plausible estimate since the alternative model provided a much better fit for the long-run convergence in wages.

[24] Again, this is calculated as $e^{(\overline{w}_1 - \overline{w}_2)} - 1$.

[25] The effect of equalizing the noise between markets is comparable to the result in Dustmann et al. (2016), who find that equalizing the variance of the signals in the external and referral market increases welfare by 0.62 percent.

The estimated impacts on average income are quite small in magnitude, especially for the alternative model. The explanations for this limited responsiveness however differ in the two cases. Since equalizing the noise terms matters little for the distribution of workers across labor market states, the effect on average income is largely driven by changes in wages within job type and therefore relatively small. In contrast, reducing the average match productivity in the referral market to the level of the external market generates two opposing effects. First, it decreases the number of workers hired through a referral as well as the wages that these workers receive. This lowers average income significantly. However, since the option value of waiting for an offer from the formerly attractive referral market is now smaller, more workers accept an offer from the external market. Furthermore, since the value of unemployment is also lower, the reservation match productivity y^* decreases so that fewer matches break up once the workers' true productivity is revealed. Both of these effects decrease unemployment and thereby increase average income.

8 Conclusion

In many labor markets around the world, referrals play a vital role in the matching between workers and firms. The analysis in this paper shows that workers who obtained their jobs through a coworker-based referral initially earn higher wages and are less likely to leave their employers than workers hired through the external market. However, as tenure increases, these initial differences decline and eventually disappear almost completely. Such dynamic patterns are consistent with the theoretical predictions of a learning model, in which referrals help to reduce uncertainty about the match-specific productivity of workers at the hiring stage, and in which firms have the ability to learn about the true productivity of their workers by observing them on the job.

To link our empirical findings back to the theory, we estimate the parameters of a structural partial equilibrium model by indirect inference, matching the full profiles of estimated data moments on relative wages and turnover probabilities to their theoretical counterparts. We also estimate an alternative model, which focuses primarily on matching the wage and turnover differences at low and high values of tenure. Our findings show that the noise in the initial signal about a worker's match-specific productivity is about 14.5 percent lower in the referral market than in the external market. The speed of learning further shows that firms learn about their workers' true match-specific productivities with a probability of 48.4 percent per year. As a result, the initial differences in wages and job turnover probabilities decrease relatively quickly and flatten out after about six years of tenure.

The baseline model does not fit the wage difference at high tenure values and thus probably over-estimates the difference in the average match productivity, with an estimated 14.0 percent higher productivity in the referral market. The alternative model, which uses a different weighting matrix of the auxiliary parameters, does a much better job in fitting the high tenure wage differential and finds that referred workers have on average a 7.6 percent higher match productivity. The differences in the noise and average match productivities are the primary driver of the initial gap in average wages (4.6 percent) and job turnover probabilities (2.3 percentage points) between referral and external hires.

Studying heterogeneity in the structural parameters across socioeconomic subgroups, we find that, in general, uncertainty about match-specific productivity is most pronounced for highly educated workers, young workers and immigrants. In contrast, we do not find any evidence for differences in terms of gender. Learning about workers' productivity is fastest for low-educated workers and immigrants and slowest for highly-educated workers. Crucially, for all socioeconomic subgroups, we find that referrals substantially reduce match-specific uncertainty and allow firms to source their new hires from a more productive pool of workers, particularly so in the high skill segment of the labor market.

Counterfactual simulations show that, in the absence of a referral market, average wages would be between 3.9 and 10.4 percent lower, primarily due to the better access to more productive workers in the referral market. Overall, our analysis shows that coworker-based referrals play an important role in the labor market by reducing information frictions and generating better and longer-lasting matches between workers and firms.

References

Antoninis, Manos, "The Wage Effects from the Use of Personal Contacts as Hiring Channels," *Journal of Economic Behavior & Organization*, 2006, *59* (1), 133–146.

Åslund, Olof and Oskar Nordström Skans, "Will I See You at Work? Ethnic Workplace Segregation in Sweden, 1985-2002," *Industrial and Labor Relations Review*, 2010, *63* (3), 471–493.

Bayer, Patrick, Stephen E. Ross, and Giorgio Topa, "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes," *Journal of Political Economy*, 2008, *116* (6), 1150–1196.

Boucher, Vincent and Marion Goussé, "Wage Dynamics and Peer Referrals," *Review of Economic Dynamics*, 2019, *31*, 1–23.

Brown, Meta, Elizabeth Setren, and Giorgio Topa, "Do Informal Referrals Lead to Better Matches? Evidence from a Firm's Employee Referral System," *Journal of Labor Economics*, 2016, *34* (1), 161–209.

Burks, Stephen V., Bo Cowgill, Mitchell Hoffman, and Michael Housman, "The Value of Hiring through Employee Referrals," *Quarterly Journal of Economics*, 2015, *130* (2), 805–839.

Calvó-Armengol, Antoni and Matthew O. Jackson, "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, 2004, *94* (3), 426–454.

Cappellari, Lorenzo and Konstantinos Tatsiramos, "With a Little Help from My Friends? Quality of Social Networks, Job Finding and Job Match Quality," *European Economic Review*, 2015, *78*, 55–75.

Carrington, William J. and Kenneth R. Troske, "On Measuring Segregation in Samples with Small Units," *Journal of Business & Economic Statistics*, 1997, *15* (4), 402–09.

Cingano, Federico and Alfonso Rosolia, "People I Know: Job Search and Social Networks," *Journal of Labor Economics*, 2012, *30* (2), 291–332.

Damm, Anna Piil, "Neighborhood Quality and Labor Market Outcomes: Evidence from Quasi-Random Neighborhood Assignment of Immigrants," *Journal of Urban Economics*, 2014, *79*, 139–166.

DeGroot, Morris H., *Optimal Statistical Decisions* 1970.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker, "Referral-based Job Search Networks," *Review of Economic Studies*, 2016, *83* (2), 514–546.

Eliason, Marcus, Lena Hensvik, Francis Kramarz, and Oskar Nordström Skans, "The Causal Impact of Social Connections on Firms' Outcomes," 2017. IFAU Working Paper 2017:11.

Galenianos, Manolis, "Learning About Match Quality and the Use of Referrals," *Review of Economic Dynamics*, 2013, *16* (4), 668–690.

Glitz, Albrecht, "Ethnic Segregation in Germany," *Labour Economics*, 2014, *29*, 28–40.

_ , "Coworker Networks in the Labour Market," *Labour Economics*, 2017, *44*, 218–230.

Gourieroux, C., A. Monfort, and E. Renault, "Indirect Inference," *Journal of Applied Econometrics*, 1993, *8*, S85–S118.

Granovetter, Mark S., *Getting a Job: A Study of Contacts and Careers*, 2 ed., University of Chicago Press, 1995.

Hellerstein, Judith and David Neumark, "Workplace Segregation in the United States: Race, Ethnicity, and Skill," *Review of Economics and Statistics*, 2008, *90* (3), 459–477.

_ , Melissa McInerney, and David Neumark, "Neighbors and Co-Workers: The Importance of Residential Labor Market Networks," *Journal of Labor Economics*, 2011, *29* (4), 659–695.

Hensvik, Lena and Oskar Nordström Skans, "Social Networks, Employee Selection, and Labor Market Outcomes," *Journal of Labor Economics*, 2016, *34* (4), 825–867.

Jovanovic, Boyan, "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 1979, *87* (5), 972–990.

Kramarz, Francis and Oskar Nordström Skans, "When Strong Ties Are Strong: Family Networks and Youth Labor Market Entry," *Review of Economic Studies*, 2014, *81* (3), 1164–1200.

Lange, Fabian, "The Speed of Employer Learning," *Journal of Labor Economics*, 2007, *25* (1), 1–35.

Marmaros, David and Bruce Sacerdote, "Peer and Social Networks in Job Search," *European Economic Review*, 2002, *46* (4-5), 870–879.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook, "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology*, 2001, *27*, 415–439.

Montgomery, James D., "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis," *American Economic Review*, 1991, *81* (5), 1407–1418.

Oyer, Paul and Scott Schaefer, "Personnel Economics: Hiring and Incentives," in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 4B, Elsevier North Holland, 2011, chapter 20, p. 1769 –1823.

Saygin, Perihan Ozge, Andrea Weber, and Michèle A. Weynandt, "Coworkers, Networks, and Job Search Outcomes," *forthcoming ILR Review*, 2019.

Schmutte, Ian M., "Job Referral Networks and the Determination of Earnings in Local Labor Markets," *Journal of Labor Economics*, 2015, *33* (1), 1–32.

Simon, Curtis J. and John T. Warner, "Matchmaker, Matchmaker: The Effect of Old Boy Networks on Job Match Quality, Earnings, and Tenure," *Journal of Labor Economics*, 1992, *10* (3), 306–330.

Topa, Giorgio, "Labor Markets and Referrals," in Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds., *Handbook of Social Economics*, 1 ed., Vol. 1, Amsterdam: Elsevier North Holland, 2011, chapter 22, pp. 1193–1221.

Wahba, Jackline and Yves Zenou, "Density, Social Networks and Job Search Methods: Theory and Application to Egypt," *Journal of Development Economics*, 2005, *78* (2), 443–473.

Appendix

A Model Details

The model presented here builds on the theoretical framework by Jovanovic (1979) and its extension by Simon and Warner (1992) and Dustmann et al. (2016). Homogeneous workers search for new jobs only while being unemployed. There are two markets through which they can receive job offers: the external (E) and the referral (R) market. Match-specific productivity, y, is drawn from a normal distribution with mean y_k and variance σ_y^2, where $k \in \{E, R\}$ refers to either the referral or external market. The model thus allows for differences in the average productivity but assumes that the underlying variance in match-specific productivity is the same in both markets. Individual productivity can then be written as $y_k = \overline{y}_k + \tau$, where $\tau \sim N(0, \sigma_y^2)$.

When workers and firms meet, they receive a noisy signal about their true match-specific productivity, $\widehat{y}_k = y_k + \varepsilon_k$, where ε_k is assumed to be normally distributed with mean zero and variance σ_k^2. The key distinction between the two markets is that the signal in the external market is more noisy than the signal in the referral market, $\sigma_R^2 < \sigma_E^2$, reflecting the fact that referrals provide information about applicants to prospective employers that they otherwise would not have. If, based on the noisy signal, a match between a worker and firm is formed, true match-specific productivity is revealed at rate α in subsequent periods.

Time is continuous (in the empirical analysis, the unit is a year) and discounted at rate r by both workers and firms. The job offer arrival rates in the referral and external markets are given exogenously by λ_R and λ_E respectively. Flow income when unemployed is given by b and employed workers earn their expected productivity. Jobs are destroyed at exogenous rate δ each period. Finally, the unemployment and employment levels are given by u and e, respectively, and the mass of workers is normalized to one.

A.1 Value Functions

Employment with Known Productivity After the true productivity y of the worker has been revealed, the value of employment is given by $W_2(y)$:

$$(r + \delta)\, W_2(y) = y + \delta U \tag{A-1}$$

where U is the value of being unemployed.

Employment with Unknown Productivity When an unemployed worker receives an offer through either of the two markets, he has to decide whether or not to take it. If the worker accepts to work for a wage equal to his expected productivity he becomes an employed worker with unknown productivity.

Let $m_k = E(y|\widehat{y}_k, k)$ denote the expected productivity given the signal and market. The value of being employed with unknown productivity through market k with expected productivity m_k is given by $W_1^k(m_k)$:

$$(r+\delta+\alpha)\,W_1^k(m_k) = m_k + \delta U + \alpha \int_{-\infty}^{\infty} max(W_2(y),U)dF_k(y|m_k)$$

where $F_k(y|m_k)$ is the distribution of true match-specific productivity given the expected productivity, m_k, which is normal with mean $\frac{\overline{y}_k\sigma_k^2+\widehat{y}_k\sigma_y^2}{\sigma_k^2+\sigma_y^2}$ and variance $\frac{\sigma_k^2\sigma_y^2}{\sigma_k^2+\sigma_y^2}$ (see DeGroot, 1970).

Unemployment The value of being unemployed is given by

$$(r+\lambda_E+\lambda_R)U = b+\lambda_R \int_{-\infty}^{\infty} max(W_1^R(m_R),U)dG_R(m_R)+\lambda_E \int_{-\infty}^{\infty} max(W_1^E(m_E),U)dG_E(m_E)$$

where G_k denotes the distribution of expected match-specific productivity in market k, which is normal with mean $\overline{y}_k$ and variance $\frac{\sigma_y^4}{\sigma_k^2+\sigma_y^2}$.

A.2 Reservation Match Qualities

When workers and firms meet, the decision of whether or not to form a match will depend on the expected match-specific productivity. If it is above the corresponding reservation expected match quality of the corresponding market, m_k^*, the worker is hired, if it is below, the worker remains unemployed. Similarly, after true match-specific productivity is revealed, the decision to continue the match depends on whether the revealed productivity is aboven or below the reservation match quality, y^*. In the following, we derive the expressions for these reservation match qualities.

Reservation Match Quality (y^*) The reservation match quality y^* after the true match-specific productivity is revealed is the value that equates the value of employment with known productivity $W_2(y)$ with the value of unemployment U. Using equation (A-1), this can be written as

$$W_2(y^*) = U = \frac{y^*}{r}.$$

The value of employment with unknown productivity can then be written as

$$\begin{aligned}(r+\delta+\alpha)\,W_1^k(m_k) &= m_k + \delta U + \alpha \int_{-\infty}^{\infty} max(W_2(y),U)dF_k(y|m_k) \\ &= m_k + (\delta+\alpha)U + \alpha \int_{y^*}^{\infty} (W_2(y)-U)\,dF_k(y|m_k) \qquad \text{(A-2)}\end{aligned}$$

where, again using Equation (A-1),

$$W_2(y) - U = \frac{y-rU}{(r+\delta)} = \frac{y-y^*}{(r+\delta)}.$$

Reservation Expected Match Quality (m_R^*, m_E^*) To derive the reservation expected match quality in the referral market, we start by rewriting the value function given in (A-2) as

$$
\begin{aligned}
(r+\delta+\alpha)\left(W_1^R(m_R)-U\right) &= m_R - rU + \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_R(y|m_R) \\
&= m_R - y^* + \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_R(y|m_R). \qquad \text{(A-3)}
\end{aligned}
$$

The reservation expected match quality m_R^* when workers and firms meet through the referral market is the value that equates the value of employment with unknown productivity $W_1^R(m_R)$ with the value of unemployment U. Using equation (A-3), we thus obtain

$$
m_R^* = y^* - \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_R(y|m_R^*)
$$

and similarly for the external market

$$
m_E^* = y^* - \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_E(y|m_E^*).
$$

These expressions for the reservation expected match qualities allow us to express the reservation match quality y^* as

$$
\begin{aligned}
y^* &= rU \\
&= b + \lambda_R \int_{m_R^*}^{\infty} (W_1^R(m) - U) dG_R + \lambda_E \int_{m_E^*}^{\infty} (W_1^E(m) - U) dG_E \\
&= b + \frac{\lambda_R}{r+\delta+\alpha} \int_{m_R^*}^{\infty} \left(m_R - y^* + \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_R(y|m_R) \right) dG_R \\
&\quad + \frac{\lambda_E}{r+\delta+\alpha} \int_{m_E^*}^{\infty} \left(m_E - y^* + \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_E(y|m_E) \right) dG_E.
\end{aligned}
$$

Given the exogenous parameters α, r, δ, λ_R, λ_E and b, the last three equations can be solved for the endogenous reservation (expected) match qualities y^*, m_R^* and m_E^*.

A.3 Comparing Reservation Expected Match Qualities

Recall that

$$
m_k^* = y^* - \alpha \int_{y^*}^{\infty} \frac{y-y^*}{(r+\delta)} dF_k(y|m_k^*) \qquad \text{(A-4)}
$$

and that $F_k(y|m_k)$, the distribution of the true match-specific productivity given the expected productivity m_k, is a normal distribution with mean $m_k = \frac{\overline{y}_k \sigma_k^2 + \widehat{y}_k \sigma_y^2}{\sigma_k^2 + \sigma_y^2}$ and variance $\frac{\sigma_k^2 \sigma_y^2}{\sigma_k^2 + \sigma_y^2}$. There are two differences between the referral market and the external market: there is less noise in the referral market than in the external market, $\sigma_R^2 < \sigma_E^2$, and the average match-specific productivity in the referral market is potentially larger than the average productivity in the external market, $\overline{y}_R > \overline{y}_E$.

Differences in the average match quality have no effect on the reservation expected match qualities in the two markets. This is because, conditional on m_k, the distribution $F_k(y|m_k)$ does not depend on $\overline{y}_k$.[26] Differences in the noise in the two markets, in contrast, have an unambiguous effect on expected reservation match qualities. In particular, according to equation (A-4), an increase in σ_k^2 implies a decrease in m_k^*.[27] Since $\sigma_R^2 < \sigma_E^2$, the reservation expected match quality in the referral market is thus higher than in the external market:

$$m_R^* > m_E^*.$$

A.4 Flow Equations

To solve for the fraction of workers in unemployment (u), employment with unknown productivity from the referred market (e_R), employment with unknown productivity from the external market (e_E), and employment with known productivity (e_2), we use the fact that in equilibrium the inflows and outflows into each of these groups have to be balanced.
The equality of inflow and outflow from unemployment is given by

$$(\delta+\alpha\frac{\int_{m_R^*}^{\infty}\int_{-\infty}^{y^*}dF_R(y|m_R)dG_R)}{1-G_R(m_R^*)})e_R+(\delta+\alpha\frac{\int_{m_E^*}^{\infty}\int_{-\infty}^{y^*}dF_E(y|m_E)dG_E)}{1-G_E(m_E^*)})e_E+\delta e_2 = \qquad \text{(A-5)}$$
$$[(\lambda_R(1-G_R(m_R^*))+\lambda_E(1-G_E(m_E^*))]u$$

The equality of inflow and outflow from employment with unknown productivity in the referral and external market is given by

$$\lambda_R(1-G_R(m_R^*))u = (\delta+\alpha)e_R \qquad \text{(A-6)}$$

and

$$\lambda_E(1-G_E(m_E^*))u = (\delta+\alpha)e_E \qquad \text{(A-7)}$$

Given the exogenous parameters α, δ, λ_R and λ_E as well as the endogenous parameters y^*, m_R^* and m_E^*, these three equations, together with the normalization of the population to one, can be solved for u, e_R, e_E, and e_2.

A.5 Simulation Details

We simulate N workers for T periods. Time is continuous and runs from $t = 0$ to T. We start by assigning an initial state at time $t = 0$ to each worker. To do that, we draw a

[26] Of course, differences in the average match quality $\overline{y}_k$ affect the frequency with which values above m_k^* are realized when workers and firms meet as well as the shape of the distribution above this cut-off as indicated by the distribution of expected match-specific productivities G_k. Hence observed average starting wages will depend on differences in the average match quality in both markets.

[27] We can prove this by contradiction. Assume that an increase in σ_k^2 leads to an increase in m_k^*. In this case, both the mean, given by m_k^* itself, and the variance of $F_k(y|m_k^*)$ in equation (A-4) will increase. This will unambiguously make the RHS decrease – which would imply a decrease in m_k^* rather than an increase.

uniformly distributed random number between 0 and 1 denoted by x. If $x \in [0, u]$ the worker is initially unemployed, if $x \in (u, u + e_R]$ the worker was hired in the referral market and has unknown productivity, if $x \in (u + e_R, u + e_R + e_E]$ the worker was hired in the external market and has unknown productivity, and if $x \in (u + e_R + e_E, u + e_R + e_E + e_2 = 1]$ the worker's productivity is known.

If the initial state is u there are no other state variables. If the state is e_k, $k \in \{R, E\}$ then the expected productivity, m_k, is drawn from a truncated normal distribution. That is $m_k \sim TN(\overline{y}_k, \frac{\sigma_y^4}{\sigma_k^2+\sigma_y^2}, m_k^*)$, where TN is a truncated normal distribution with mean $\overline{y}_k$, variance $\frac{\sigma_y^4}{\sigma_k^2+\sigma_y^2}$, and truncation from below at m_k^*. From here the true productivity is drawn from $N(m_k, \frac{\sigma_k^2\sigma_y^2}{\sigma_k^2+\sigma_y^2})$.

If the state is e_2 we need to know the true productivity y. This is a complicated object, since there have been two preceding stages of selection from the initial distribution of y. To deal with this, we first assign the previous state before e_2. Let e_2^R be the fraction of workers in the state with known productivity that comes from the referral market. This can be calculated as $e_2^R = \frac{\frac{\int_{m_R^*}^{\infty}\int_{y^*}^{\infty} dF_R(y|m_R)dG_R}{1-G_R(m_R^*)}e_R}{\frac{\int_{m_R^*}^{\infty}\int_{y^*}^{\infty} dF_R(y|m_R)dG_R}{1-G_R(m_R^*)}e_R+\frac{\int_{m_E^*}^{\infty}\int_{y^*}^{\infty} dF_E(y|m_E)dG_E}{1-G_E(m_E^*)}e_E}$. The expected productivity is then drawn in the following way. First, the true productivity y_k is drawn from a normal distribution $N(\overline{y}_k, \sigma_y^2)$, then the observed signal is created as $\widehat{y}_k = y_k + \mathrm{N}(0, \sigma_k^2)$. From this, the expected productivity is given by $m_k = \overline{y}_k + (\widehat{y}_k - \overline{y}_k)\frac{\sigma_y^2}{\sigma_k^2+\sigma_y^2}$. We now need to condition on the match having reached the state with unknown productivity and the state with known productivity. Thus, if $m_k < m_k^*$ or $y < y^*$, we redraw the values and continue with this until both values are sufficiently high.

Following these steps, we now have the true and expected productivities of all workers in the initial steady state. In the next step, we need to simulate worker histories until time T.

Worker Paths In general, workers can be hit by four different shocks in the model. The length of each spell is determined by the Poisson rates λ_E, λ_R, δ and α. Since the waiting time until the next event occurs is exponentially distributed, the spell lengths until each shock are independent and can be found as the inverse of the exponential CDF. Thus, for the random numbers $x_i \sim U[0, 1]$, $i = 1, ..4$, the lengths of an unemployment spell, an employment spell in the first stage and an employment spell in the second stage are given by: $t_{\text{unempl}} = \min\{\frac{-\log(1-x_1)}{\lambda_E}, \frac{-\log(1-x_2)}{\lambda_R}\}$, $t_{e_1} = \min\{\frac{-\log(1-x_3)}{\alpha}, \frac{-\log(1-x_4)}{\delta}\}$, $t_{e_2} = \min\{\frac{-\log(1-x_4)}{\delta}\}$ respectively.[28] Take as an example an unemployed worker at time 0. He is in this state until time t_{unempl} when a job offer arrives. If $\frac{-\log(1-x_1)}{\lambda_E} < \frac{-\log(1-x_2)}{\lambda_R}$ the job offer is from the external market (otherwise, it is from the referral market). The unemployed worker then draws an expected and true productivity denoted m_E and y_E. If $m_E < m_E^*$ he rejects the

[28] We do not need to know all spell lengths for all workers in all states. For instance, for a worker in the state with known productivity, we only need to know t_{e_2}. However, due to vectorizations and computer efficiency, it is faster to just compute all three lengths.

job offer. If not, he continues into employment with unknown productivity in the external market. He is in this state from time t_{unempl} until time $t_{\text{unempl}} + t_{e_1}$, where t_{e_1} is calculated based on a new random draw of x_i. If $\frac{-\log(1-x_3)}{\alpha} > \frac{-\log(1-x_4)}{\delta}$, the match dissolves exogenously and the worker becomes unemployed. If $\frac{-\log(1-x_3)}{\alpha} < \frac{-\log(1-x_4)}{\delta}$, the shock is a revelation shock and the true productivity becomes known. If $y < y^*$, the match dissolves. If $y \geq y^*$, the match continues in the state with known productivity for a duration of t_{e_2} (but the wage changes). This process continues until all workers have lived through a pre-specified end time denoted by T. Note that the first spell of a worker is always censored because the starting date of the spell is unknown.

A.6 Moments

In this section, we describe how we compute the moments in the simulated data. Let t denote the cross-sectional periods from 0 to T with unit increments. Let N denote the number of workers (2 million), J_i the number of jobs of worker i, $K_{it} \in \{E, R, U\}$ the current state of the worker (in external job, in referral job, or unemployed), and $k \in \{E, R\}$ the market through which a job was found, either the external (E) or the referral (R) market. Let S_{ijt} denote the (approximate) tenure of worker i in job j at time t.[29] Then the mean wage is given as the average over all cross-sectional spells with tenure less than or equal to 10:

$$\overline{w} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{t=0}^{T} w_{ijt} \mathbb{I}(S_{ijt} \leq 10) \mathbb{I}(S_{ijt} \leq t)}{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{t=0}^{T} \mathbb{I}(S_{ijt} \leq 10) \mathbb{I}(S_{ijt} \leq t)},$$

where the term $\mathbb{I}(S_{ijt} \leq t)$ ensures that we only include spells in the calculation of the average wage which were started during our sample period.

The average wage of jobs encountered through market k for a given tenure s is given by:

$$\overline{w}_k(s) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{t=0}^{T} w_{ijt} \mathbb{I}(K_{it} = k) \mathbb{I}(S_{ijt} = s) \mathbb{I}(S_{ijt} \leq t)}{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{t=0}^{T} \mathbb{I}(K_{it} = k) \mathbb{I}(S_{ijt} = s) \mathbb{I}(S_{ijt} \leq t)}$$

and the hazard rates are calculated as:

$$h_k(s) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{t=0}^{T-1} \mathbb{I}(K_{it} = k) \mathbb{I}(S_{ijt} = s) \mathbb{I}(S_{ijt} \leq t) \mathbb{I}(K_{i(t,t+1]} = U)}{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{t=0}^{T-1} \mathbb{I}(K_{it} = k) \mathbb{I}(S_{ijt} = s) \mathbb{I}(S_{ijt} \leq t)}$$

Finally, the probability $PrUE_k$ is given by:

$$PrUE_k = \frac{\sum_{i=1}^{N} \sum_{t=1}^{\text{T-1}} \mathbb{I}(K_{it-1} = E \cup K_{it-1} = R) \mathbb{I}(K_{it} = U) \mathbb{I}(K_{it+1} = k)}{\sum_{i=1}^{N} \sum_{t=1}^{\text{T-1}} \mathbb{I}(K_{it-1} = E \cup K_{it-1} = R) \mathbb{I}(K_{it} = U)}.$$

[29] Approximate tenure is real tenure rounded down to the closest integer. We are forced to work with approximate tenure due to the structure of our data. For example, if a worker started a new job in the summer of year t, the first time we would observe the worker in this job in our data would be in the cross-section for November of year t where we would then record his tenure as 0.

B Moment Fit

Table B-1: Model Fit: Baseline Model

Wages			Turnover		
Moment	Simulation	Data	Moment	Simulation	Data
$\overline{w}_R(0) - \overline{w}_E(0)$	0.064	0.045	$h_R(0) - h_E(0)$	-0.015	-0.023
$\overline{w}_R(1) - \overline{w}_E(1)$	0.045	0.035	$h_R(1) - h_E(1)$	-0.010	-0.021
$\overline{w}_R(2) - \overline{w}_E(2)$	0.030	0.027	$h_R(2) - h_E(2)$	-0.006	-0.016
$\overline{w}_R(3) - \overline{w}_E(3)$	0.021	0.019	$h_R(3) - h_E(3)$	-0.003	-0.010
$\overline{w}_R(4) - \overline{w}_E(4)$	0.015	0.011	$h_R(4) - h_E(4)$	-0.002	-0.007
$\overline{w}_R(5) - \overline{w}_E(5)$	0.013	0.007	$h_R(5) - h_E(5)$	-0.001	-0.002
$\overline{w}_R(6) - \overline{w}_E(6)$	0.011	0.003	$h_R(6) - h_E(6)$	-0.001	-0.003
$\overline{w}_R(7) - \overline{w}_E(7)$	0.010	-0.003	$h_R(7) - h_E(7)$	-0.000	0.000
$\overline{w}_R(8) - \overline{w}_E(8)$	0.010	-0.005	$h_R(8) - h_E(8)$	0.000	0.002
$\overline{w}_R(9) - \overline{w}_E(9)$	0.009	-0.006	$h_R(9) - h_E(9)$	0.000	0.006
$\overline{w}_R(10) - \overline{w}_E(10)$	0.009	-0.007	$h_R(10) - h_E(10)$	-0.000	0.003
$\overline{w}_E(0)$	4.831	4.908	$h_E(0)$	0.288	0.461
$\overline{w}_E(1)$	4.961	4.970	$h_E(1)$	0.244	0.336
$\overline{w}_E(2)$	5.045	5.017	$h_E(2)$	0.215	0.267
$\overline{w}_E(3)$	5.094	5.052	$h_E(3)$	0.199	0.227
$\overline{w}_E(4)$	5.121	5.080	$h_E(4)$	0.189	0.196
$\overline{w}_E(5)$	5.136	5.103	$h_E(5)$	0.185	0.173
$\overline{w}_E(6)$	5.143	5.125	$h_E(6)$	0.182	0.157
$\overline{w}_E(7)$	5.147	5.149	$h_E(7)$	0.181	0.142
$\overline{w}_E(8)$	5.149	5.171	$h_E(8)$	0.180	0.130
$\overline{w}_E(9)$	5.150	5.193	$h_E(9)$	0.180	0.122
$\overline{w}_E(10)$	5.151	5.211	$h_E(10)$	0.179	0.114
$\overline{w}$	4.997	5.007			
$PrUE_R$	0.109	0.072			
$PrUE_E$	0.394	0.365			

Note: Wage and turnover differences correspond to the estimates depicted in Figure 4. $\overline{w}_k(s)$ and $h_k(s)$ is the average wage and hazard rate for workers with tenure s hired through market k. $\overline{w}$ is the average wage. $PrUE_k$ is the probability of having a job in market k at time $t+1$ given the worker was unemployed at time t. The simulations are performed for 105 million workers. The auxiliary parameters are described in detail in Appendix A.6 and the weighting matrix is an identity matrix.

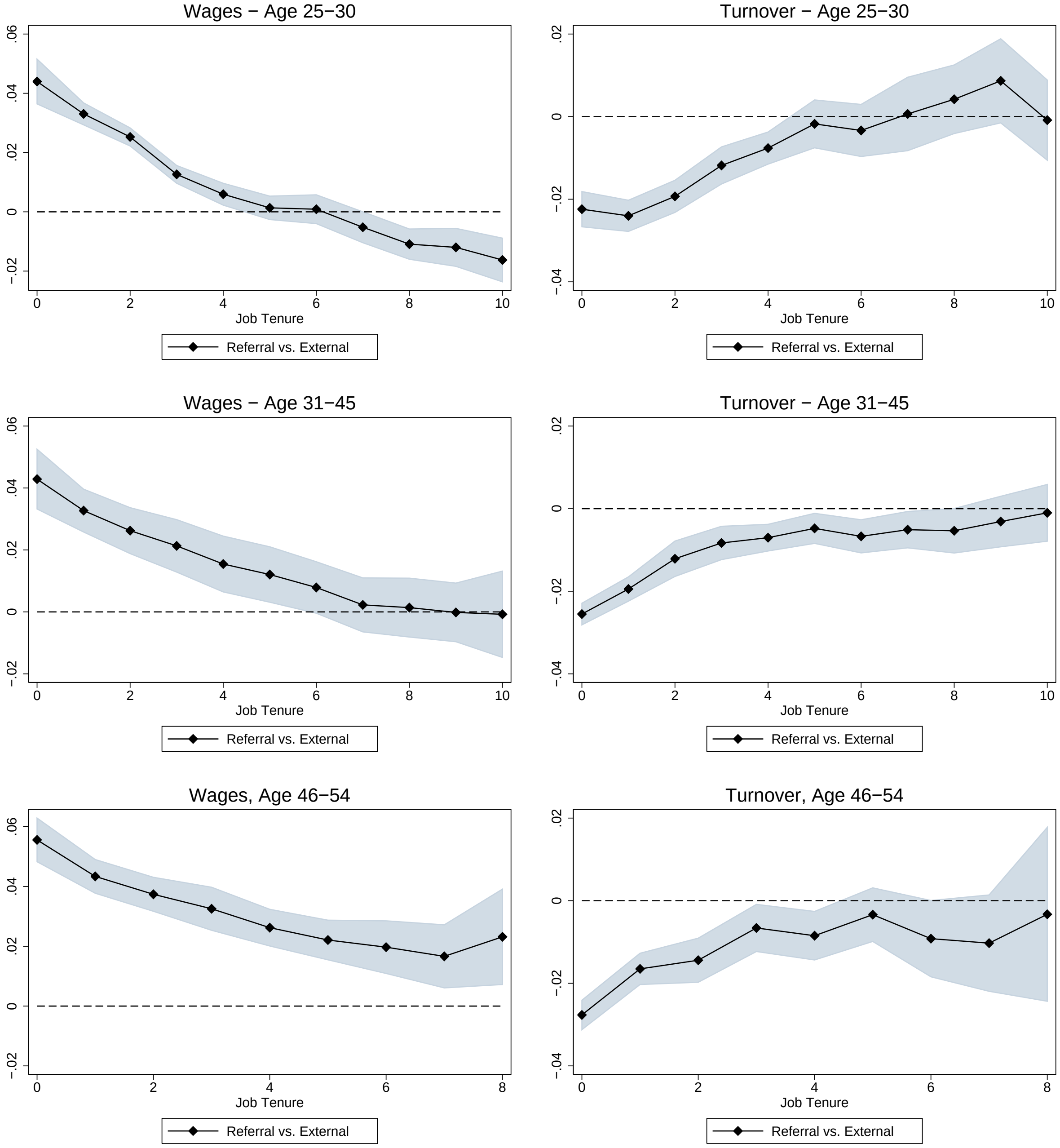
Table B-2: Moment Fit: Alternative Model

Wages				Turnover			
Moment	Simulation	Data	Weight	Moment	Simulation	Data	Weight
$\overline{w}_R(0) - \overline{w}_E(0)$	0.055	0.045	100	$h_R(0) - h_E(0)$	-0.017	-0.023	100
$\overline{w}_R(1) - \overline{w}_E(1)$	0.023	0.035	0	$h_R(1) - h_E(1)$	-0.008	-0.021	0
$\overline{w}_R(2) - \overline{w}_E(2)$	0.007	0.027	0	$h_R(2) - h_E(2)$	-0.003	-0.016	0
$\overline{w}_R(3) - \overline{w}_E(3)$	0.001	0.019	0	$h_R(3) - h_E(3)$	-0.001	-0.010	0
$\overline{w}_R(4) - \overline{w}_E(4)$	-0.001	0.011	0	$h_R(4) - h_E(4)$	-0.000	-0.007	0
$\overline{w}_R(5) - \overline{w}_E(5)$	-0.002	0.007	0	$h_R(5) - h_E(5)$	-0.000	-0.002	0
$\overline{w}_R(6) - \overline{w}_E(6)$	-0.002	0.003	0	$h_R(6) - h_E(6)$	0.000	-0.003	0
$\overline{w}_R(7) - \overline{w}_E(7)$	-0.002	-0.003	0	$h_R(7) - h_E(7)$	0.000	0.000	0
$\overline{w}_R(8) - \overline{w}_E(8)$	-0.002	-0.005	0	$h_R(8) - h_E(8)$	0.000	0.002	0
$\overline{w}_R(9) - \overline{w}_E(9)$	-0.001	-0.006	0	$h_R(9) - h_E(9)$	-0.000	0.006	0
$\overline{w}_R(10) - \overline{w}_E(10)$	-0.001	-0.007	100	$h_R(10) - h_E(10)$	0.000	0.003	100
$\overline{w}_E(0)$	4.912	4.908	1	$h_E(0)$	0.320	0.461	1
$\overline{w}_E(1)$	5.055	4.970	0	$h_E(1)$	0.265	0.336	0
$\overline{w}_E(2)$	5.115	5.017	0	$h_E(2)$	0.242	0.267	0
$\overline{w}_E(3)$	5.138	5.052	0	$h_E(3)$	0.234	0.227	0
$\overline{w}_E(4)$	5.146	5.080	0	$h_E(4)$	0.230	0.196	0
$\overline{w}_E(5)$	5.149	5.103	0	$h_E(5)$	0.229	0.173	0
$\overline{w}_E(6)$	5.150	5.125	0	$h_E(6)$	0.229	0.157	0
$\overline{w}_E(7)$	5.150	5.149	0	$h_E(7)$	0.229	0.142	0
$\overline{w}_E(8)$	5.151	5.171	0	$h_E(8)$	0.228	0.130	0
$\overline{w}_E(9)$	5.151	5.193	0	$h_E(9)$	0.229	0.122	0
$\overline{w}_E(10)$	5.150	5.211	1	$h_E(10)$	0.228	0.114	1
$\overline{w}$	5.048	5.007	1				
$PrUE_R$	0.081	0.072	1				
$PrUE_E$	0.354	0.365	1				

Note: Wage and turnover differences correspond to the estimates depicted in Figure 4. $\overline{w}_k(s)$ and $h_k(s)$ is the average wage and hazard rate for workers with tenure s hired in market k. $\overline{w}$ is the average wage. $PrUE_k$ is the probability of having a job in market k at time $t+1$ given the worker was unemployed at time t. The simulations are performed for 105 million workers. The auxiliary parameters are described in detail in Appendix A.6. The weighting matrix is a diagonal matrix with weights as indicated by the table.

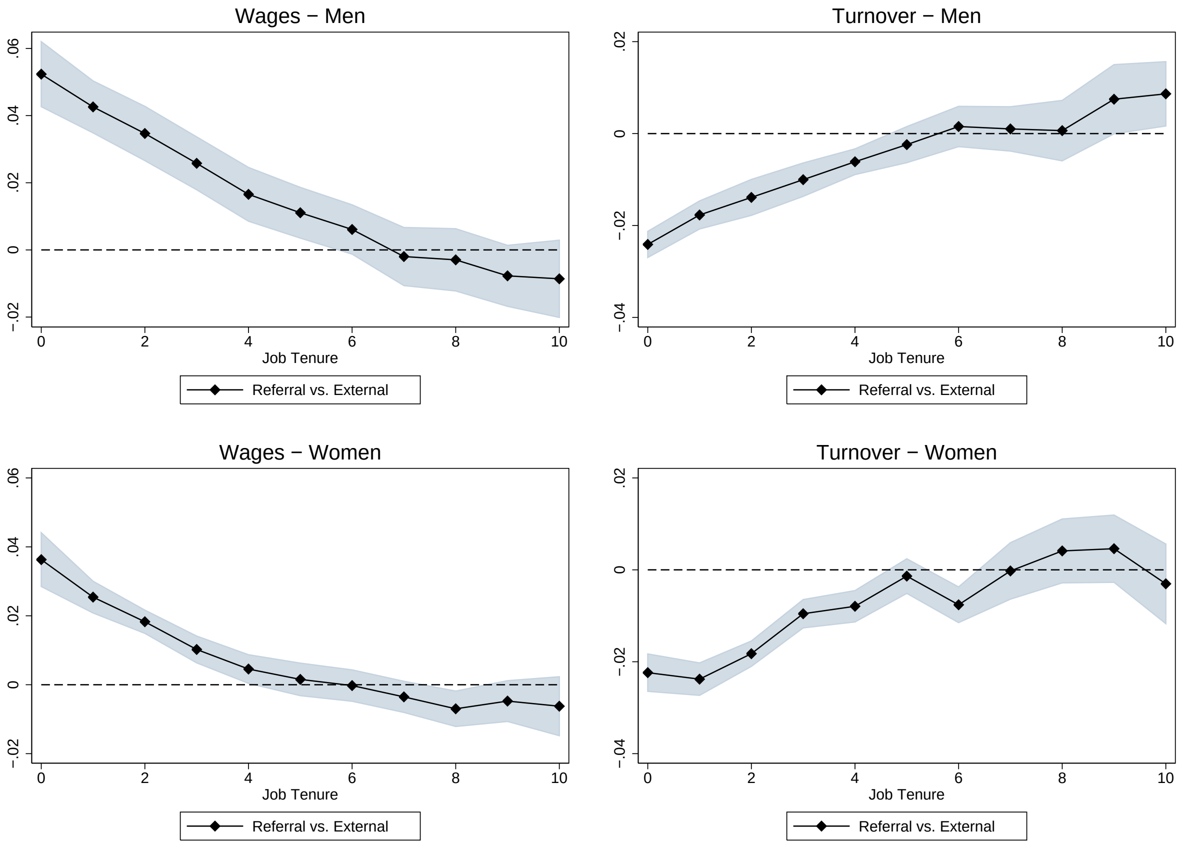
C Additional Results

Figure C-1: Convergence Profiles - Age Groups



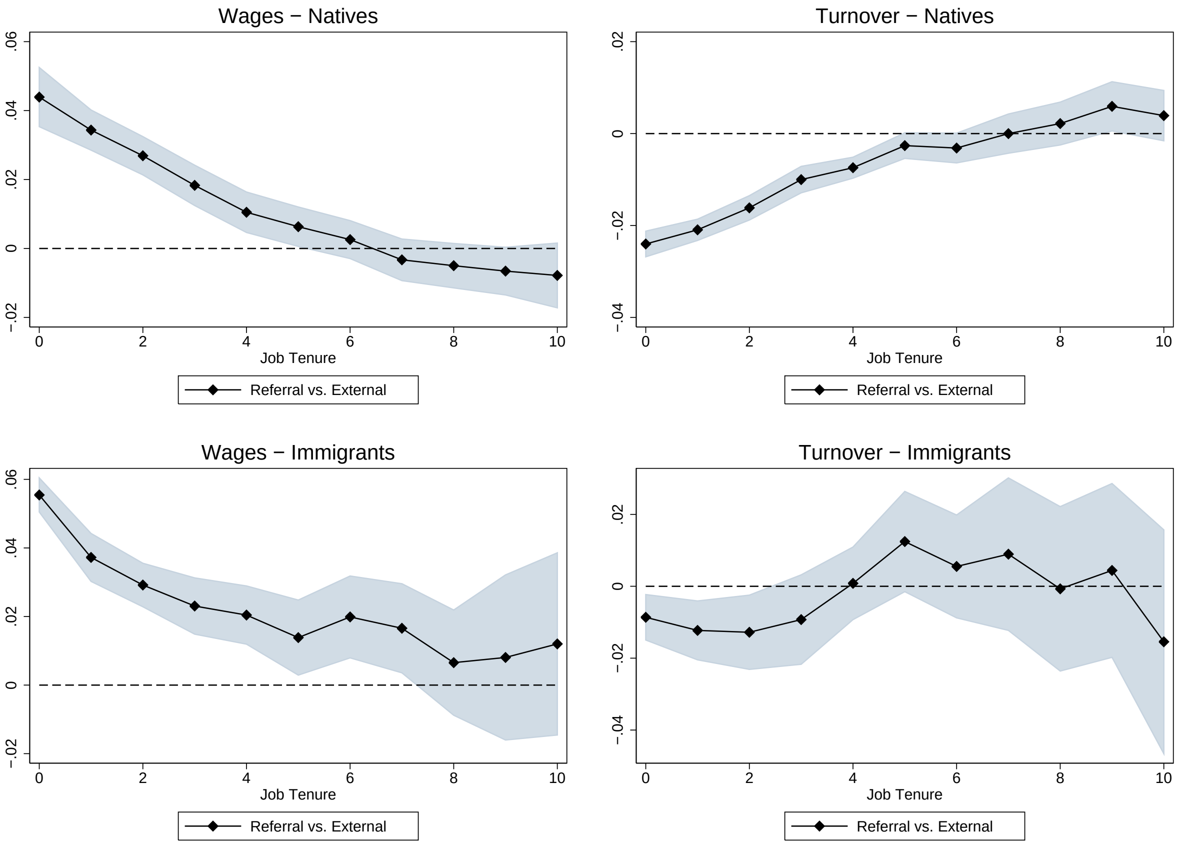
Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile. Because the overall sample is restricted to workers aged 25 to 54, the maximum duration of tenure observable for the group of workers aged 46 to 54 at the time of hiring is eight years.

Figure C-2: Convergence Profiles - Gender



Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile.

Figure C-3: Convergence Profiles - Immigrants



Note: Reported coefficients and confidence intervals taken from a regression that includes the same controls as those reported in columns (3) and (6) of Table 3 but rather than controlling for quadratic tenure, age, accumulated experience and accumulated occupational experience profiles, it controls fully non-parametrically for all of these effects. The estimation sample excludes movers with a network size beyond the 99th percentile.