Referral-based Job Search Networks

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Abstract

This paper derives novel testable implications of referral-based job search networks in which employees provide employers with information about potential new hires that they otherwise would not have. Using comprehensive matched employer-employee data covering the entire workforce in one large metropolitan labor market combined with unique survey data linked to administrative records, we provide evidence that workers earn higher wages and are less inclined to leave their firms if they have obtained their job through a referral. These effects are particularly strong at the beginning of the employment relationship and decline with tenure in the firm, suggesting that firms and workers learn about workers' productivity over time. Overall, our findings imply that job search networks help to reduce informational deficiencies in the labor market and lead to productivity gains for workers and firms.

Key Words: Networks, Referrals, Uncertainty

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1 Introduction

Several studies show that at least one third of employees have obtained their current job through family members or friends, pointing towards the importance of informal social networks in the job search process.[1] Such networks may serve as an information transmission mechanism and therefore have the potential to enhance the efficiency of the labor market by reducing informational uncertainties and search frictions. So far, however, little is known about how job search networks actually operate, and whether they indeed lead to efficiency gains.

In this paper, we focus on an information transmission mechanism in which employees refer network members to their employers and thereby provide them with information about potential job market candidates that they otherwise would not have, as in the referral models by Montgomery (1991), Simon and Warner (1992) and, more recently, Galenianos (2013).[2] Similar to Borjas (1992, 1995), Bertrand et al. (2000), and Bandiera et al. (2009), we define networks in terms of ethnicity. Based on a search model that encompasses both uncertainty in the labor market and the possibility of hiring through either formal channels or through the network, we propose novel empirical implications of referral-based job search networks. We test these implications using both large-scale matched employer-employee social security data covering all workers and firms in one large German metropolitan area over a 20 year period, and unique survey data linked to social security records. Our most conservative estimates show that referrals lead to around 2.5 percent higher initial wages and a 1.9 percentage point lower initial probability of leaving one's firm. Consistent with our theoretical framework, both of these initial gains from referrals decline over time spent in the firm.

Our model builds on the learning-matching model by Jovanovic (1979, 1984). We extend his analysis by distinguishing between recruitment through networks and through

[1]See, for instance, Granovetter (1974, 1995), Corcoran et al. (1980), Holzer (1988), Gregg and Wadsworth (1996), and Addison and Portugal (2002). For recent surveys of the literature, see also Ioannides and Loury (2004) or Topa (2011).

[2]An alternative way of how information can be exchanged within networks is among potential employees by informing each other about job opportunities, as in Topa (2001) and Calvó-Armengol and Jackson (2004, 2007).

the external market, and by endogenizing the probability of obtaining a job through a referral and relating it to the workforce composition of the firm. In our model, the worker's match-specific productivity is more uncertain in the external than in the referral market. This larger uncertainty implies a larger opportunity for future wage growth, as workers are partially insured against low realizations of their productivity by quitting their job (see Jovanovic 1979, 1984). Consequently, referral hires turn down wage offers that otherwise identical external hires would accept and are therefore initially better matched than external hires. But since low realizations of the match-specific productivity lead, over time, to separations of the least suitable workers from their firms, the difference in match quality, and hence in wages and turnover probabilities, between external and referral hires declines with tenure in the firm.

We confirm the key predictions of our model based on analysis of two complementary data sources, using alternative estimation approaches. First, motivated by our theoretical model and confirmed by empirical evidence from two novel survey data sets linked to social security records, we use the share of workers from the same ethnic group in the firm at the time of the hire as a proxy for a referral hire. Second, we use direct information on referrals obtained from linked survey-social security data. Both approaches show that referral hires earn higher wages, but experience slower wage growth, than external hires once we account for the non-randomness of workers' sorting into firms and use of referrals. Furthermore, referral hires are initially less likely to leave their firms than external hires, but this effect also declines with tenure in the firm.

According to our most conservative estimate, we compute that uncertainty in the referral market is 41.4 percent lower than in the external market, and that referrals, through the provision of additional information to employers, increase total welfare in the economy by 0.62 percent. Overall, the combined evidence from the large-scale matched employer-employee data and the smaller linked survey-social security data provide strong evidence for the hypothesis that, through referrals, job search networks help to reduce informational deficiencies in the labor market and lead to productivity gains for workers and firms.

Our paper is related to the literature on job search networks. Most of the existing evidence on such networks comes from surveys where *workers* are asked how they found their current job (see Ioannides and Loury, 2004, for an excellent overview). While the widespread use of social contacts in the job search process is a consistent finding, the evidence on its effect on wages is mixed. For instance, while Marmaros and Sacerdote (2002) report that individuals who received help from fraternity/sorority contacts were more likely to obtain high-paying jobs, Bentolila et al. (2010) find significant wage discounts for jobs found through family and friends.[3] One concern in this literature is that both employees and employers who rely more on networks in their job search process may not be randomly selected. An important contribution of our paper is that the longitudinal nature of our data allows us to eliminate any potential bias due to the fact that low productivity workers, or low productivity firms, may use networks in their job search process more or less intensively than high productivity workers and firms. Our results illustrate that addressing selection is indeed important, and that the different ways to deal with it may be one reason for some of the contradictory findings in the literature.

While most studies rely on *worker* surveys to analyze job search networks, two recent studies by Brown et al. (2014) and Burks et al. (2015) use data from a single (or a set of) firms that include explicit information about whether or not a new hire was referred by a current employee, and find evidence in line with ours. Since these papers compare the wage and turnover behavior of referred and non-referred workers within the same firm, they are, like us, able to account for the possible non-random selection of firms into the recruiting method. We add to these studies by additionally accounting for the possible non-random selection of workers, by investigating the effects of a referral on wage and turnover trajectories for a representative set of firms, and by providing a theoretical framework that allows us to interpret our findings in a concise manner.

Other recent research does not use direct information on the job search method used, but instead provides indirect, yet compelling, evidence on the existence of job search

[3]Other papers with varying findings include Holzer (1987), Kugler (2003), Loury (2006) and Patel and Vella (2013). Pellizzari (2010) provides an overview of wage differentials between jobs found through informal and formal methods in a number of European countries, and Topa (2011) provides a comprehensive survey of this literature.

methods. For instance, while Bayer et al. (2008) and Hellerstein et al. (2011) show that network members cluster together in the same work-location or firm, Kramarz and Skans (2013) find that firms are more likely to hire children of current employees than otherwise comparable job candidates. In a similar spirit, Oyer and Schaefer (2009) present evidence that partners hire graduates from their own law school with a much higher probability than randomization would predict. We complement these studies by analyzing ethnicity-based (as opposed to location-, family- or education-based) networks and go beyond these papers by presenting novel evidence on the productivity of networks.[4]

A number of recent papers provide, like our paper, both a theoretical and empirical analysis on the use of networks in the labor market, but focus on different mechanisms than us. For instance, while Hensvik and Skans (2013) systematically test and provide support for Montgomery's (1991) referral model whereby referrals allow firms to attract workers with high unobserved (to the market) productivity, Heath (2013) provides evidence that firms use referrals in order to mitigate limited liability (moral hazard) problems. Schmutte (2014) develops a search model in which workers who are connected to workers earning high wages are assumed to draw from a better wage offer distribution than workers who are connected to workers earning low wages, while Goel and Lang (2009) focus on the effects of networks on wages which arise through the number of job offers strongly and weakly connected workers may receive. Bandiera et al. (2009) and Beaman and Magruder (2012) study how favoritism or the type of referral changes in response to different incentive schemes.

The structure of the paper is as follows. In the next section, we set up a referral model that forms the basis of our empirical analysis. After describing the data and main minority groups, we provide comprehensive survey evidence of the relevance of ethnicity-based networks in the job search process in Germany in Section 3. We then explain our empirical methods in Section 4 and report the corresponding results as well as their

[4] In a field experiment for a specific online market, Pallais and Sands (2014) show that referred workers perform better on the job than *all* other workers who applied for the job. Although consistent with ours, Pallais and Sands's findings suggest that referred workers are more productive than the average *job applicant*, while our findings (and those of Brown et al., 2014, and Burks et al., 2015) suggest that referred workers are (initially) more productive than workers *who obtained the job* through other channels.

welfare implications in Section 5. Section 6 concludes.

2 Theory

This section sets up a job search model in which workers provide otherwise unobservable information about the productivity of their network members to the employer. Our model builds on Simon and Warner (1992) and the learning model by Jovanovic (1979, 1984). We extend Jovanovic's analysis by distinguishing between recruitment through networks and through the external market, and by endogenizing the probability of obtaining a job through a referral and relating it to the workforce composition of the firm.

2.1 Set-up

The economy consists of N workers and L firms which produce with a constant returns to scale production function. There is free entry of vacancies. Firms and workers live forever, are risk-neutral, and maximize expected profits and expected utility, respectively. There are two groups of workers, minority and majority workers.

Each period, workers choose between employment and unemployment, while firms decide whether or not to post a vacancy. Workers receive unemployment benefit b during unemployment. Firms incur a vacancy cost k each period a position remains unfilled.

Productivity y is match-specific and drawn from a normal distribution with mean μ and variance σ_μ^2. When a firm and a worker meet, they observe a noisy signal $\widehat{y} = y + \varepsilon$ about the worker's productivity, where ε is normally distributed with mean 0 and variance σ_i^2. Firms can hire either through the referral ($i = R$) or through the external ($i = E$) market. Referrals provide employers with information that they otherwise would not have. We model this as a more precise signal in the referral than in the external market, i.e. $\sigma_R^2 < \sigma_E^2$. In order to focus on the role of information, we assume that the mean of the productivity distribution is the same in the referral and external market. Firms and workers use the signal to update their belief about the worker's productivity. We denote this updated belief by $m = E(y|\widehat{y})$. Let $F_i(y|m_i, \sigma_i^2)$, $i = R, E$, denote the distribution of the worker's true productivity y, given that her expected productivity is m_i.[5]

Each period, firms and workers fully learn about the worker's true productivity with probability α. With probability δ, the job ends for exogenous reasons. Wages are determined through Nash bargaining, where γ denotes the share of the total surplus that is captured by workers.

We assume a particularly simple network structure: each worker is connected to only one worker. The network is ethnicity-based: minority workers are only connected to minority workers, and majority workers are only connected to majority workers. We make both assumptions for convenience only, and none of our implications depends on them (see Appendix A.4). The assumption required is that minority workers are more likely to be connected to other minority workers than majority workers are. There is strong evidence in favor of this assumption, which we will discuss in detail in Section 3.2.

The timing of events in each period is as follows.

1. For each vacancy, the firm randomly picks an employee and asks him for a referral. If the firm has v_l vacancies, then v_l employees are simultaneously chosen out of the firm's existing workforce. If the worker connected to this employee is unemployed, the firm and this worker meet. If she is employed, the firm hires through the external market.[6]

2. Firm and worker observe a signal about the productivity of the referred worker. The firm makes a wage offer. If the worker turns down the wage offer, the position remains vacant and the worker remains unemployed.

3. Workers who have not received a referral offer (u_E), and vacancies to which no worker was referred (v_E), enter the external market where firms and workers randomly meet through a constant returns to scale matching function $m(u_E, v_E)$. Firms and workers observe a signal about the worker's productivity, and firms make a wage

[5] From DeGroot (1970), F_i is normally distributed with mean $\frac{\mu\sigma_i^2+\tilde{y}\sigma_\mu^2}{\sigma_i^2+\sigma_\mu^2}$, and variance $\frac{\sigma_\mu^2\sigma_i^2}{\sigma_\mu^2+\sigma_i^2}$.

[6] Note that the firm's expected value of the match is higher in the referral than in the external market. Hence, firms have an incentive to first try to fill the position through referrals before they enter the external market. For a more general setting in which firms endogenously choose the method through which they search, see Galenianos (2013).

offer. If the workers decline the wage offers, the positions remain vacant and the workers remain unemployed.

4. In the next period, employees and firms learn the employee's true productivity with probability α. Firms make a new wage offer. If the employee turns down the wage offer, she becomes unemployed, and the position becomes vacant.

5. With probability δ, the match is destroyed for exogenous reasons.

2.2 Value Functions and Optimal Search Behavior

We begin with the decision problem of workers and firms just after the worker's true productivity y has been revealed. With probability $(1-\delta)$, the match survives and the value of the match remains unchanged. With probability δ, the job is destroyed for exogenous reasons. In this case, workers become unemployed and the position becomes vacant. The worker's and the firm's value of the match, W_2 and J_2, therefore equal:

$$\begin{aligned} W_2 &= w_2 + \beta(1-\delta)W_2 + \beta\delta U, \text{ and} \\ J_2 &= y - w_2 + \beta(1-\delta)J_2 + \beta\delta V, \end{aligned}$$

where w_2 denotes the wage paid to the worker, β is the discount factor, U is the value of being unemployed, and V is the value of a vacancy. Workers capture the share γ of the total surplus so that wages are determined by:

$$W_2 - U = \gamma(W_2 - U + J_2),$$

where we use the fact that free entry drives V to zero. There is a reservation match quality y^* such that, if $y > y^*$, workers prefer to stay and firms prefer to keep the worker, where y^* satisfies $W_2(y^*) - U = 0$ and $J_2(y^*) = 0$. It should be noted that y^* is the same for workers who were hired through the referral or the external market.

Next, consider the decision problem of workers and firms who have just met through the external market, and the worker's expected productivity is m_E. If hired, the worker will earn wage w_E in the current period. Next period, the job is destroyed for exogenous reasons with probability δ and the worker becomes unemployed. With probability $(1-\alpha)(1-\delta)$, the job survives, firms and workers receive no new information about the worker's productivity, and the worker's value of the match remains unchanged. With probability $\alpha(1-\delta)$, the job survives and the worker's productivity is revealed. In this case, the worker can choose between W_2 and U. The worker's value of the match therefore equals:

$$W_{1,E} = w_E + \beta(1-\alpha)(1-\delta)W_{1,E} + \beta\alpha(1-\delta)\int \max(W_2, U)dF_E(y|m_E, \sigma_E^2) + \beta\delta U.$$

The firm's value of the match can be similarly derived as

$$J_{1,E} = m_E - w_E + \beta(1-\alpha)(1-\delta)J_{1,E} + \beta\alpha(1-\delta)\int \max(J_2, 0)dF_E(y|m_E, \sigma_E^2).$$

Wages are determined by Nash bargaining:

$$W_{1,E} - U = \gamma(W_{1,E} - U + J_{1,E}).$$

There is a reservation expected match quality m_E^* such that, if $m > m_E^*$, workers prefer to accept the wage offer and firms prefer to hire the worker, where m_E^* satisfies $W_{1,E}(m_E^*) - U = 0$ and $J_{1,E}(m_E^*) = 0$.

For the decision problem of workers and firms that have met through the referral market, the worker's and firm's value of the match, $W_{1,R}$ and $J_{1,R}$, can be derived accordingly; see equations (A-1) and (A-2) in Appendix A.1. Again, there is a reservation expected match quality m_R^* such that, if $m > m_R^*$, workers accept the wage offer and firms are willing to employ the worker, where m_R^* satisfies $W_{1,R}(m_R^*) - U = 0$ and $J_{1,R}(m_R^*) = 0$.

As we show in Appendix A.2, the two reservation expected match qualities in the external and the referral market are given by

$$m_i^* = y^* - \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)}\int_{y^*}^{\infty}(y-y^*)dF_i(y|m_i^*, \sigma_i^2) \qquad i = R, E, \qquad (1)$$

where the last term is a positive function of σ_i^2, the noise of the productivity signal.

We derive the value of unemployment U in Appendix A.1; see equation (A-4). We focus on the steady state equilibrium where the unemployment rate u is constant over time.[7] Equations (A-9) and (A-10) in Appendix A.3 show the outflow out of and inflow into unemployment in each period.

2.3 Empirical Implications

The key implications we test in the empirical analysis concern the wage and turnover dynamics of workers hired through the referral market compared to those of workers hired through the external market. These implications are a consequence of the signal about the worker's productivity being less noisy in the referral than in the external market (i.e., $\sigma_R^2 < \sigma_E^2$). Because of the higher precision of the signal, the reservation match quality in the referral market is higher than the reservation match quality in the external market (i.e., $m_R^* > m_E^*$, see equation (1) and Appendix A.2 for a formal proof). The intuition for this result is simple: a larger uncertainty of the worker's productivity implies a larger opportunity for future wage growth since workers are partially insured against low realizations of their productivity by leaving the firm (Jovanovic 1979, 1984). Workers are therefore willing to accept worse matches if the uncertainty of the match is higher.

Since $m_R^* > m_E^*$, referral hires are on average better matched with their firm than external hires. Hence, they earn higher wages and are less likely to leave the firm than external hires. More specifically, since only workers whose productivity has not been revealed yet are better matched, workers who obtained their job through a referral initially earn higher wages, and are less likely to switch firms than workers hired through the external market, but these effects decline with tenure as firms and workers gradually get to know the worker's true productivity (see also Appendix A.2).[8] It should be noted that

[7] For a theoretical analysis that explicitly studies the effectiveness of the referral channel over the business cycle, see Galenianos (2014).

[8] We have abstracted from on-the-job search. While including job-to-job transitions complicates the theoretical analysis considerably, it does not alter our empirical predictions. Workers who obtained their job through a referral will, at the beginning of the employment relationship, be better matched on average, than workers who obtained their job through the external market. They therefore earn a higher

while an initially higher wage for referral hires than for external hires also follows from the homophily model of referrals by Montgomery (1991) (in this model, referrals allow firms to attract workers with high unobserved productivity), the fading-out of the referral effect with tenure is unique to our model.[9]

3 Data and Descriptive Evidence

3.1 Data

3.1.1 Matched Employer-Employee Data

The first data source we use in our analysis is a matched employer-employee data set covering more than two decades, from 1980 to 2001. It comprises every man and woman covered by the social security system, observed on the 30th of June in each year.[10] In addition to unique worker and firm identifiers[11], the data include an unusually wide array of background characteristics, such as education[12], occupation, and industry. Our definition of minority groups is based on citizenship. Consequently, individuals with foreign citizenship who were born in Germany are included among the minority populations. The citizenship variable is very detailed, distinguishing between 203 groups. Wages reported are gross daily wages and are right censored at the social security contribution ceiling. For a detailed description of the data set, see Bender et al. (2000).

wage and are less likely to move from job-to-job and from job-to-unemployment at the beginning of the employment relationship.

[9]Montgomery (1991) does not model firm turnover; his model therefore has no explicit predictions regarding the probability that a worker will stay with the firm. Alternative referral models based on favoritism (e.g. Beaman and Magruder, 2012) or moral hazard considerations (e.g. Heath, 2013) are either silent on the effect of a referral on initial wages and turnover and their subsequent trajectories, or predict markedly different patterns than those predicted by our model. See Brown et al. (2014), for an overview of the different model predictions.

[10]In 2001, 77.2 percent of all workers in the German economy were covered by social security and are hence recorded in the data (Bundesagentur für Arbeit, 2004). Not included are civil servants, the self-employed, and military personnel.

[11]To be precise, the "firm" identifier refers to establishments. Throughout the paper, we use the terms workplace, establishments, and firms interchangeably.

[12]To improve the consistency of the education variable in our data and in order to be able to consistently allocate workers into skill groups, we set for each worker her education variable to the maximum observed over the sample period. As standard in the German context, "low-skilled" refers to workers without any vocational training, "medium-skilled" refers to workers with vocational training, and "high-skilled" refers to workers with college education.

The data are particularly suited for our analysis. First, we observe every worker in every firm, which ensures our findings are representative for both firms and workers, and allows us to precisely calculate the ethnic composition of each firm's workforce. Second, we are able to follow workers and firms over time.

From this data base, we selected all workers aged between 15 and 64 working full-time in one of the four largest metropolitan areas in West Germany: Hamburg, Cologne, Frankfurt, and Munich. This strategy is motivated as follows. First, mobility to and from these cities is fairly low, around 2.8 percent in one year and 6.9 percent over 5 years. Hence, we can think of these cities as local labor markets. Second, minorities are concentrated in large cities: while 23.2 percent of minorities live in the four largest cities, only 13.9 percent of Germans do. Throughout the paper, we focus on findings for the Munich metropolitan area which consists of 10 districts, 222 municipalities, and is approximately 70 miles in diameter. Baseline results for the other three metropolitan areas are similar, and can be found in Appendix C (Table A.2).

Minority workers comprise 16.3 percent of workers in our sample. They predominantly originate from Germany's traditional guest worker countries—Turkey, Yugoslavia, Italy, Greece, Spain and Portugal—which provide 64 percent of all minority workers in the sample; see column (1) of Table A.1 in the data appendix for details. Active recruitment of guest workers from these countries started in the mid-1950s as a result of the strong economic growth at the time but came to a hold following the recession in 1973/1974. However, subsequent immigration of family members continued.[13]

3.1.2 Survey Data Linked to Social Security Records

Our second data source links social security data with two survey data sets, the PASS-IEB data, collected between 2007 (wave 1) and 2012 (wave 6), and the IAB-SOEP Migration Sample, collected in 2013. By linking two of the best known German household surveys, the PASS and the SOEP, to the German social security records, the resulting data sets combine the extensive information of each individual survey with the detailed work

[13] For more detailed information on the different migration waves and their historical background, see Bauer et al. (2005).

history information of the social security data. In comparison to the matched employer-employee data, both linked data sets are smaller in sample size. Moreover, unlike the matched employer-employee data, the linked surveys focus on particular subgroups of the population: the IAB-SOEP Migration Sample is restricted to immigrant respondents and the PASS-IEB sample, while containing information on both German and immigrant respondents, significantly oversamples households of welfare recipients due to its overall focus on welfare and poverty.

The key advantage of the two linked survey-social security data sets over the matched employer-employee data is that they contain direct information on referrals. However, the information provided in the two surveys is slightly different in that the question of whether a job was obtained through a referral in the PASS-IEB sample refers to the current job of the respondent whereas it refers to the first job obtained after an immigrant's arrival in Germany in the IAB-SOEP Migration Sample.[14] The combination of social security records with survey data containing information on referrals is unique and has to our knowledge not been exploited in the literature. We provide more information on both data sets in Appendix B, where we also describe how the surveys were linked to the administrative records.

For our analysis, we have selected all full-time workers aged between 15 and 64 with valid information on their job search method. Our final sample based on the PASS-IEB data consists of 1,373 workers, of whom 349 are minority workers, while our final sample based on the IAB-SOEP data comprises 404 minority workers. In addition to the traditional guest worker groups dominating in the matched employer-employee data, both linked survey-social security samples comprise also populations of more recent minority groups, in particular from Eastern Europe, whose inflow started in the late 1980s as a result of the collapse of the Former Soviet Union and the political changes in the former Eastern Bloc (see columns (2) and (3) of Table A.1). Note that for both German and minority workers, median firm tenure is considerably lower in our PASS-IEB sample than in the matched employer-employee sample, 0.75 years compared to between 2 and 3 years

[14] Information on referrals is available in the PASS-IEB data for waves 3, 5 and 6.

respectively, in part reflecting the PASS-IEB's focus on individuals with low attachment to the labor market.

3.2 Survey Evidence on Referrals and Ethnic Networks

In Table 1, Panel A, we provide evidence that referrals play an important part in the hiring process. According to the PASS-IEB data, 28.7 percent of minority workers obtained their *current* job through acquaintances, friends or relatives, compared to 25.3 percent of German workers. With 46.8 percent, this share is considerably higher in the IAB-SOEP Migration Sample for the *first* job after arrival in Germany, suggesting that immigrant's reliance on social contacts is particularly strong when they enter the country. For completeness, we also display results based on the standard German SOEP. According to this data source, 42.7 percent of minority workers found their current job through the social network—a figure that lies between those found in the two other data sources. All three data sets reveal that the use of social contacts for job search purposes is particularly pronounced among low-skilled workers and least pronounced among high-skilled workers (e.g., 35.3 percent vs. 19.6 percent in the PASS-IEB data).

Our theoretical model assumes that referrals are predominantly made on behalf of workers with the same minority background. Panel B in Table 1 shows that 61.7 percent of the foreign citizens in the standard SOEP samples for the years 1996 and 2001 name someone who is also non-German as their first befriended person, compared to only 4.9 percent of the German citizens.[15] Importantly, the vast majority of those 61.7 percent of non-German friends (91.7 percent) come from the same country of origin as the respondents, strongly supporting the notion that immigrants' social contacts are ethnicity-based.[16] This pattern even applies to minority groups that have already been in Germany for an extended period of time, such as those from guest worker countries, those who have been in Germany for more than 10 years, and those born in Germany.

[15] The standard German SOEP regularly collects detailed information about the structure of social contacts individuals maintain. In those modules, respondents are asked to name their first, second, and third friend, and to state the origin of these friends. If they are not of German origin, respondents are specifically asked whether they themselves come from the same country of origin as their cited friends.

[16] The corresponding figures for the second and third befriended person are similar in magnitude, with 59.5 (91.2) and 61.0 (89.9) percent, respectively.

Overall, the survey evidence suggests that social networks are an important feature of the job search process, and that these networks are, for minority workers, predominantly based on ethnic similarity, a finding in line with survey evidence from other data sources and countries.[17]

4 Empirical Strategy

The main implications of our model are that referral hires initially earn higher wages and are less likely to leave their firms than external hires, and that, because of learning, these effects decline with tenure. To test these predictions, we ideally would like to estimate the following baseline regression:

$$y_{ijt} = \beta_0 + \beta_1 Ref_{ij}^{\tau} + \beta_2 Ref_{ij}^{\tau} \cdot tenure_{ijt} + X_{ijt}'\beta_3 + \gamma_t + \delta_i + f_j + \varepsilon_{ijt}, \tag{2}$$

where y_{ijt} is either the log daily wage of worker i or an indicator variable equal to 1 if the worker leaves the firm in $t+1$, Ref_{ij}^{τ} is an indicator variable equal to 1 if the worker obtained her job at firm j starting in year τ through a referral, and X_{ijt} is a vector of (possibly) worker-, firm-, and time-varying control variables (such as tenure). Finally, γ_t, δ_i, and f_j denote year, worker, and firm fixed effects, respectively, and ε_{igjt} is an unobserved error term.

The key parameters of interest are β_1 and β_2, where β_1 measures the impact of a referral on the worker's log wage or turnover decision in the first year of the employment relationship, while β_2 measures how this impact changes with tenure in the firm. We expect $\beta_1 > 0$ in the wage regression and $\beta_1 < 0$ in the turnover regression (because referred workers are initially better matched); further, $\beta_2 < 0$ in the wage regression and $\beta_2 > 0$ in the turnover regression (because firms and workers learn over time).

[17] The importance of referrals has not only been confirmed in a variety of worker surveys, such as the NLSY or PSID for the U.S. (e.g. Corcoran et al., 1980, Holzer, 1987, Mouw, 2003, or Loury, 2006), the LFS for the UK (e.g. Gregg and Wadsworth, 1996), or the European Community Household Panel (e.g. Pellizzari, 2010), but also in firm surveys, such as the German IAB Establishment Panel (see Fischer et al., 2008) or the National Organizations Survey (e.g. Marsden, 2001). In addition, there is extensive sociological evidence for the hypothesis that social networks operate along ethnicity lines (for a review, see McPherson et al., 2001).

To account for the possible non-random sorting of referral hires into firms which may bias the wage and turnover effects of referrals, one would like to control for both worker and firm fixed effects. The inclusion of worker fixed effects δ_i allows for the possibility that, in line with the observation that the use of referrals is particularly pronounced among the low-skilled, low-ability workers rely more heavily on referrals in the job search process than high-ability workers. Including fixed firm effects f_j accounts for low- and high-productivity firms making use of referrals to a different extent.[18] Unfortunately, there is no data source which allows us to directly estimate the regressions given by equation (2). Next, we describe two complementary estimation strategies, each with advantages and disadvantages, that both come close to estimating such regressions.

4.1 Analysis Based on Matched Employer-Employee Data

A first approach is based on the matched employer-employee data. The advantage of this data source is that it is large in scale and representative for all workers and firms covered by the social security system in the four metropolitan areas we focus on. Since we follow the same workers and firms over many years in the labor market, this data source further allows us to simultaneously estimate the worker and firm fixed effects δ_i and f_j in equation (2). The disadvantage of this data source is that it does not contain direct information on whether or not the individual obtained her job through a referral. To deal with this issue, we use a proxy for a referral that we can observe in the matched employer-employee data and that is motivated by our theoretical model: the share of workers from the same minority group in the firm one period before the worker was hired. We denote this proxy by $S_{gj}^{\tau-1}$, where as before the superscript τ refers to the year the worker was hired at firm j, and the subscript g denotes the minority group the worker belongs to. According to our model, the probability that a minority worker from group g who was hired in period

[18]The importance of controlling for firm fixed effects when estimating the effect of referrals on wages is emphasized by Galenianos (2013) who shows that, in a model in which firms endogenously choose the signal accuracy they obtain in the formal market, high productivity firms use referrals to a lesser extent than low productivity firms.

τ obtained the job through a referral equals: [19]

$$\Pr(\text{Referral}|\text{Hire}_j^\tau\text{=Minority}_g) = \frac{S_{gj}^{\tau-1} u \Pr(m > m_R^*)}{S_{gj}^{\tau-1} u \Pr(m > m_R^*) + S_g(1-u)\lambda_E^F \Pr(m > m_E^*)}, \quad (3)$$

where u denotes the steady-state unemployment rate and λ_E^F the probability that the firm meets a worker through the external market. The denominator is the overall probability that a minority worker was hired (with S_g denoting the overall share of minority workers from group g in the population), while the numerator is the probability that a minority worker was hired through the referral market. The probability that a minority worker obtained her job through a referral is thus increasing in the share of minority workers in the firm at $\tau - 1$. The intuition for this result is simple: since minority workers refer workers from their own group to the employer, the higher is the share of minority workers from group g in the firm, the more likely is the firm to meet workers from group g through referrals.

We provide two pieces of evidence, one indirect and one direct, that support the use of the share of co-workers from the own ethnic group as a proxy for a referral. First, if the own group share is positively related to a referral, then we should observe that firms which employed a higher share of minority workers from a specific group in the past also hire more workers from that group in the future. This is just another implication of the assumption that workers from a particular minority group refer workers from their own group to the firm. According to our model, the probability that a minority worker from group g, as opposed to a majority worker or minority worker from a different group, is hired equals:

$$\Pr(\text{Hire}_j^\tau\text{=Minority}_g) = \frac{S_{gj}^{\tau-1} u \Pr(m > m_R^*) + S_g(1-u)\lambda_E^F \Pr(m > m_E^*)}{u \Pr(m > m_R^*) + (1-u)\lambda_E^F \Pr(m > m_E^*)}, \quad (4)$$

where the denominator is the overall probability that a worker, regardless of which group, is hired, either through the referral or the external market[20], and the numerator is the

[19]Here, we have assumed that minority workers only refer workers from their own group to their employer.

[20]The probability that a referred worker is recruited is equal to the probability that the connection of

probability that a minority worker from group g is hired. The probability that the position is filled with a minority worker from group g, rather than a worker from a different group, is therefore increasing in the share of existing minority workers from that group in the firm, $S_{gj}^{\tau-1}$. We provide empirical support for such persistence in the firm's hiring behavior in Section 5.1.1. In order to provide more direct evidence in favor of our proxy, we investigate in a second step whether the probability of having obtained a job through the referral market is indeed positively related to the share of workers from the same minority group in the firm one period before the worker was hired, using the PASS-IEB data and the IAB-SOEP Migration Sample linked to social security records (Section 5.1.1).

After having established that the own minority share in a firm helps to predict the probability of having obtained a job through a referral, we then proceed to estimating regressions of the type shown in equation (2), where we replace the probability of having obtained the job through a referral, Ref_{ij}^{τ}, with our proxy $S_{gj}^{\tau-1}$. For the proxy to be valid, we require the additional assumption that conditional on worker and firm fixed effects and the other control variables in regression (2), the share of co-workers from the own type in the firm prior to being hired has no direct effect on wage and turnover dynamics but affects these only through its impact on referrals. Thus, the worker and firm effects play an additional role in the regressions based on the proxy for a referral relative to the regressions based on direct information on referrals. The inclusion of worker fixed effects does not only account for the possibility that low-ability workers may be more likely to make use of referrals than high-ability workers, but also for the possibility that low-ability workers systematically sort into firms employing more workers of their own type. Similarly, the inclusion of firm fixed effects does not only allow for the possibility that low-productivity firms may be more likely to utilize referrals than high-productivity firms, but also for the possibility that low-productivity firms systematically employ a large share of minority workers from the same type. Hence, if worker and firm effects

the employee chosen to recommend a worker is unemployed, u, times the probability that this worker's expected productivity exceeds the reservation match quality, m_R^*. The probability that a worker is hired through the external market is the product of the probability that no worker was referred to the position, $1-u$, the probability that the firm meets a worker through the external market, λ_E^F, and the probability that the worker's expected productivity exceeds the reservation match quality, m_E^*.

are not conditioned on in regressions of type (2), the share of co-workers from the own type may not only reflect the impact of referrals on wages and turnover dynamics, but also the non-random sorting of workers to firms. The inclusion of these fixed effects, on the other hand, eliminates any bias due to non-random sorting based on permanent differences across workers and firms.

Estimating fixed worker and firm effects in large samples as ours is computationally intensive, which has prompted Abowd et al. (1999) to rely on approximate solutions. We instead employ the algorithm proposed by Abowd et al. (2002) that calculates the exact solution of equation (2).[21] This procedure does not yield standard errors. We obtain these via bootstrapping with 50 repetitions.[22]

When estimating equation (2), we pool all workers, including German workers, in our sample and interact all variables in (2) with a dummy variable indicating whether the worker is from a minority group. Including Germans in the estimation sample implies that both minority and German workers are used to estimate the fixed firm effects, leading to more precise estimates. Our estimation sample spans the years 1990 to 2001. In order to ensure that we observe the share of workers from the same minority group one period before the worker is hired, we restrict the sample to workers who joined their firm after 1980, the first year available in the data, and whose firm already existed in the year before the worker was hired.[23] We further restrict the sample to low- and medium-skilled workers because of wage censoring. This affects about 50 percent of the high-skilled, but less than 7 percent of the medium-skilled and 3 percent of the low-skilled.[24] Our share variable refers to all workers in the firm, and is computed before these sample restrictions are imposed.

[21]The algorithm is based on the iterative conjugate gradient method and exploits that, due to the large number of dummy variables, the design matrix is sparse.

[22]In our baseline regressions, standard errors are very similar when we use 100 repetitions.

[23]We include all workers who joined their firm after 1980 in the sample but let our estimation only cover the period 1990 to 2001 to maintain a representative sample with respect to firm tenure. The lagged minority shares, however, are calculated using the whole population of workers.

[24]For minority workers, wage censoring is lower, with 3.5 percent of the medium-skilled and 1.9 percent of the low-skilled being affected. We drop these censored observations from the sample.

4.2 Analysis Based on Linked PASS-IEB Data

Our second approach to test the key implications of our model is based on the linked survey-social security data from the PASS-IEB. The key advantage of this data set is that it contains direct information on referrals. However, compared to the matched employer-employee data, this data source is much smaller in scale and oversamples workers less attached to the labor market (see Section 3.1.2). Moreover, because of the limited scope of the sample and the fact that only few workers are observed multiple times, we are not able to account for worker and firm fixed effects in the estimation in the same way as in our analysis above. We proceed instead in two alternative ways. First, we use only those job spells for which we observe whether or not a worker obtained her job through a referral and estimate our baseline regression (2) based on this restricted sample. To still be able to address the firm and worker selection into referral use, we include pre-estimated worker and firm fixed effects as additional control variables. We obtain these by first separately estimating wage and turnover regressions based on 6-year windows of the *universe* of social security records.[25] Depending on the outcome variable we study, we then merge to each worker in the PASS-IEB data who starts a new job in period τ the estimated worker and firm fixed effects from the corresponding wage or turnover regression estimated over the time window $\tau - 1$ to $\tau - 7$. The outcome-specific fixed effects therefore pre-date the job spells used in the subsequent estimation of equation (2), and serve as proxies for unobserved heterogeneity in terms of wage potential and turnover probability. Since information on referrals in our second linked survey data set, the IAB-SOEP Migration Sample, exists only for the first job upon arrival, this strategy is not feasible for this data source.

In an alternative procedure, we add to the restricted PASS-IEB sample for which we observe whether the worker obtained the job through a referral all *other* social security records of full-time workers aged 15 to 64 between 2002 and 2012, even though for these spells we do not know through which job search method the worker obtained the job.

[25] As in our main sample, the social security records refer to the 30th of June. In addition to the worker and firm fixed effects, we control for age squared and year dummies in the log wage and turnover regressions.

These added spells include both workers who later enter the PASS-IEB survey and for whom we thus observe the use of referrals for some spells, and co-workers of participants of the PASS-IEB survey. Even though the job search method is not known for these spells, they are nevertheless helpful in identifying the fixed worker and firm effects. Using this extended data set, we re-estimate our baseline wage regression in equation (2), now jointly estimating the fixed worker and firm effects, and replacing Ref_{ij}^{τ} using two dummy variables, one that is equal to 1 if the worker obtained the job through a referral and another one that is equal to 1 if the worker did not use her social network to find the job. All remaining spells which appear in the social security data but not in the PASS-IEB data—and for which the referral status is unknown—form the base category. When presenting results from this estimation, we report the differences between the coefficients on the two dummy variables, both for the effect of referrals on initial wages and wage growth. We perform this analysis only for wages and not for turnover, since monthly information on firm tenure is only available for the spells that are part of the PASS-IEB data but not for the added social security spells referring to the 30th of June which contain only *yearly* information on firm tenure. Monthly information, however, is crucial to identify the effects of referrals on turnover in the PASS-IEB sample where 58 percent of workers leave their firm within the first year. To increase the sample size, we include both minority and German workers in all wage and turnover estimations based on the PASS-IEB Data.

5 Results

We now turn to testing the key predictions of our model: referral hires initially earn higher wages and are less likely to leave the firm than external hires, but these effects decline with tenure. We first report results based on the matched employer-employee data, using the share of workers from the same minority group in the firm at the time of the hire as a proxy for a referral. We then turn to results from the PASS-IEB survey linked to social security records, using direct information on how the worker obtained her job.

5.1 Results Based on Matched Employer-Employee Data

Before we report our baseline results, we first provide descriptive evidence in support of using the share of workers from the own minority group as a proxy for a referral.

5.1.1 The Own Group Share as a Proxy for a Referral

If the own group share is positively related to the probability of having obtained the job through a referral, then firms which employed a higher share of minority workers from a specific group in the past will be more likely to hire more workers from that group also in the future (see equation (4)). We provide evidence for such persistence in hiring in Table 2 in which we report results from the following regression:

$$H_{gj}^{\tau} = \alpha_0 + \alpha_1 S_{gj}^{\tau-1} + X_j^{\prime\tau}\alpha_{2g} + Z_{gj}^{\prime\tau-1}\alpha_3 + \gamma_g^{\tau} + u_{gj}^{\tau}, \tag{5}$$

where H_{gj}^{τ} is the share of minority workers from group g among all new hires in firm j at time τ, $S_{gj}^{\tau-1}$ is the share of minority workers from the same group in the firm in $\tau-1$, one period before the worker was hired, $X_j^{\prime\tau}$ is a vector of demand side control variables, $Z_{gj}^{\prime\tau-1}$ is a vector of supply side control variables, γ_g^{τ} denote minority group specific year fixed effects, and u_{gj}^{τ} is an unobserved error term. The parameter of interest is α_1, which identifies the probability of obtaining a job through a referral: $\alpha_1 = \frac{u\Pr(m>m_R^*)}{u\Pr(m>m_R^*)+(1-u)\lambda_E^F\Pr(m>m_E^*)}$.[26] For the empirical analysis, we focus on the five main minority groups in the metropolitan area: Yugoslavs, Turks, Italians, Austrians and Greeks.[27]

Table 2 provides strong evidence that firms' hiring behavior in the past helps to predict whom firms hire in the future. While column (1) controls only for minority group

[26] We show in Appendix A.4 that the close connection between α_1 and the probability of obtaining a job through a referral holds under a more general network structure than the one assumed, for example if workers are connected to more than one worker or if networks are only partially ethnicity-based.

[27] Consequently, we have five observations (one for each minority group) per firm that hired at least one worker (German or minority) in a given year. Together, the five main minority groups make up 69 percent of all minority observations in the sample. We have also carried out the analysis for the 15 biggest minority groups, which make up 85 percent of all minority observations, with very similar results.

specific year fixed effects (a specification that arises directly from the theoretical model and equation (4)), column (2) adds an extensive set of demand and supply side control variables, X_j^τ and $Z_{gj}^{\tau-1}$, and column (3) adds the joint share of workers from all other minority groups to proxy for the degree of openness of the firm to non-German workers.[28] Estimates do not change much across specifications. The results in column (2) indicate that an increase in the existing share of workers from a particular minority group in the firm by 10 percentage points increases the share of minority workers from that group among all new hires in the firm by 4.98 percentage points.[29] As explained above, this parameter estimate can be interpreted as 49.8 percent of minority workers obtaining their job through a referral, a value similar to the 46.8 percent and 42.7 percent reported in the IAB-SOEP Migration Sample and the standard SOEP, but larger that the 28.7 percent reported in the PASS-IEB data (see Panel A, Table 1).

Our matched survey-administrative data provide us with the opportunity to investigate whether the own minority share in a firm is indeed a good proxy for the probability of having obtained a job through a referral. Table 3 reports regressions of the referral probabilities (from the survey data) on the own minority share (from the administrative data). Starting with the PASS-IEB data, the first column in Table 3 shows that a 10 percentage point increase in the own minority share in the firm in the year before the hire is associated with a 10.9 percentage point higher probability that a minority worker of that group obtained the job through a referral. This coefficient remains almost unchanged after controlling for a worker's gender, educational attainment and age as well as the log size of the firm and the industry in which it operates (column (2)), and pre-estimated fixed worker and firm effects as described in Section 4.2 (column (3)). Not surprisingly, there is no significant relationship between the share of German workers in the firm in the year before the hire and the probability that a German worker relied on her social network to find the job, justifying our focus on minority workers when using the matched employer-employee data.

[28]Variables included in X_j^τ and $Z_{gj}'^{\tau-1}$ are explained in the note of Table 2.

[29]Results for the specification in column (2) for the three other metropolitan areas give very similar results, with coefficient estimates of around 0.5.

Columns (4) and (5) show the corresponding results based on the IAB-SOEP Migration Sample, which only includes minority workers. The association between the own minority share in the firm and the referral probability in this sample is highly significant, but only about half as large as in the PASS-IEB data. This could be because measurement error is higher in the IAB-SOEP Migration Sample than in the PASS-IEB data, since, in contrast to the PASS-IEB data, the information on the job search method is asked only retrospectively and refers to the immigrant's first job upon arrival in Germany.

Overall, Table 3 provides strong direct support for the theoretical link established in Section 2 between a worker's own minority share prior to hiring and the probability of having obtained the job through a referral.

5.1.2 Wages and Turnover

How then does the share of workers from the same minority group one year before the worker was hired affect wages and turnover decisions of minority workers? In Panel A in Table 4, we report the *overall* impact of this share (that is, without the tenure interaction in equation (2)). We start with OLS estimates and, in addition to the own share, only control for year fixed effects (column (1)). The estimate points to a strong negative association between the own share and wages. Including a full set of control variables[30] reduces this parameter estimate in magnitude by about half (column (2)). Controlling for worker fixed effects in column (3) leads to a substantial further reduction in the magnitude of the estimated parameter. If we include a full set of firm fixed effects instead of the worker fixed effects (column (4)), the impact of the share of workers from the same minority group on wages turns positive. As described in Section 4, our preferred final specification includes both worker and firm fixed effects and is shown in column (5). The estimate implies that an increase in the share of workers from the same minority group in the firm at the time of the referral by 10 percentage points (which roughly corresponds to an increase of half a standard deviation) increases the wage of minority workers by 0.43 percent. The significant change in our parameter estimate due to the

[30] These covariates are: the log of the firm size, industry dummies, 5 firm tenure categories (0 years, 1-2 years, 3-4 years, 5-9 years, $\geq$10 years), age, age squared, education dummies and a gender indicator.

inclusion of control variables suggests that the sorting of workers into firms is important, and that OLS estimates are therefore biased.

Turning to the turnover regressions, once we control for both worker and firm fixed effects, we find that an increase in the own share by 10 percentage points reduces the probability of leaving the firm by 0.22 percentage points, with the effect being statistically significant at the 10 percent level. As before, the OLS results in columns (1) to (3), which do not account for sorting, result in estimates of opposite sign.

If firms and workers learn about workers' productivity over time, the wage gains due to an increase in the share of workers from the same minority group in the firm one year before the worker was hired should be concentrated at the beginning of the employment relationship and decline with tenure. Similarly, a higher own share should reduce the probability of leaving one's firm initially, but less and less so with tenure. We confirm these predictions in Panel B of Table 4, where we include an interaction term between the own share and tenure as an additional regressor. Focusing on the specification that includes both firm and worker fixed effects (column (5)), an increase in the own share by 10 percentage points raises wages by 0.66 percent and reduces turnover by 0.52 percentage points at the beginning of the employment relationships. Both effects rapidly decrease with tenure.[31]

In Panel C of Table 4, we investigate this issue in a slightly different manner, by allowing the impact of the own share to vary between a worker's first year at the firm and a worker's subsequent years at the firm. The mean wage in subsequent years is a weighted average of the mean wage of workers whose productivity has not been revealed yet, and the mean wage of workers whose productivity is known and who have decided to stay with the firm, where a greater weight is given to the latter if the learning rate (α) is higher (see equation (A-12) in Appendix A.5). In line with the estimates from Panel B, we find that once we include firm and worker fixed effects, a 10 percentage point increase in the initial share of workers of the own type raises wages in the first year

[31] The wage estimate implies that after 3 1/3 years, the effect should become negative. Note however that average firm tenure in the data is only 3.1 years, so that the average worker hired through a referral does not experience a wage penalty at the end of her employment relationship.

by 0.69 percent, compared to only 0.10 percent in subsequent years. We find a similar pattern for turnover: a 10 percentage point increase in the own share lowers turnover in the first year by 0.64 percentage points, and increases turnover in subsequent years.

In Appendix C, we show that the same patterns also emerge in the other metropolitan areas (Table A.2). We further demonstrate that our findings are robust to a number of specification checks (Table A.3).

5.1.3 Magnitude of Findings

To assess how much a *referral* increases wages and reduces turnover, we propose a data-based and a model-based method, which—as we argue below—provide upper and lower bounds of the true effects of a referral.

Our findings in Table 3 based on the PASS-IEB data suggest that a 10 percentage point increase in the share of workers from the same minority group in the firm at the time of the hire increases the probability that a minority worker obtained a job through a referral by 9.8 percentage points (column (3)). Transforming the results in Table 4 using the data-based transformation factor (0.10/0.098) = 1.02, the estimates reported in column (5) of Panel B thus imply that a referral raises wages of workers in their first year at the firm by 6.7 (3.4) percent (standard error in parentheses) and reduces subsequent wage growth by 2.0 (1.0) percentage points per year. It further lowers initial turnover by 5.3 (3.0) percentage points, or 18.8 percent of the annual turnover probability of 28.2 percent, and leads to a 2.6 (1.3) percentage point relative annual increase in job turnover probability in subsequent years.[32]

Our model provides an alternative way of assessing by how much a 10 percentage point increase in the share of the own minority group increases the probability that a minority worker relied on her social network to find the job, which at 26.9 percentage points is 2.7 times larger than the value suggested by the PASS-IEB data.[33] Transforming the

[32]Standard errors are calculated using the delta method.

[33]According to equation (3), $\Pr(\text{Referral}|\text{Hire}_j^\tau\text{=Minority}_g) = \frac{S_{gj}^{\tau-1}}{S_{gj}^{\tau-1}+S\frac{b}{a}}$, where $a = u\Pr(m > m_R^*)$ and $b = (1-u)\lambda_E^F \Pr(m > m_E^*)$. Furthermore, from Table 2 and equation (4), we obtain $\alpha_1 = \frac{a}{a+b} = 0.498$, so that $\frac{b}{a} = \frac{1-\alpha_1}{\alpha_1} = 1.008$. When evaluating equation (3) at the median minority share in the firm prior to the hire in our sample, $\tilde{S}_{gj}^{\tau-1} = 2.8$ percent, and the median share of minority workers in the

effect of the own minority share in Table 4 into the effect of a referral by multiplying each estimate with the corresponding model-based transformation factor ($0.10/0.269 = 0.37$), we thus find smaller effects: a referral increases wages by initially 2.5 (0.3) percent, reduces subsequent wage growth by 0.7 (0.03) percent, lowers initial turnover by 1.9 (0.5) percentage points (or 6.7 percent of the annual turnover probability of 28.2 percent), and leads to a 1.0 (0.1) percentage point relative annual increase in job turnover probability in subsequent years.

While the data-based method is likely to overestimate the true effect of a referral, the model-based method is likely to underestimate it. Due to measurement error induced by inevitable errors in linking self-reported information on the current job to their social security records, the 9.8 percentage point increase in the probability of having obtained a job through a referral is likely an underestimate, leading to an overestimate of the data-based effect of referrals on wages and turnover. On the other hand, the model-based transformation attributes the persistence in hiring solely to selective referrals. If there are other reasons for why workers from the same minority groups cluster together in the same firms for which we are unable to adequately control in our hiring regressions, this transformation overestimates the effect of the minority share in the firm on the referral probability and thus underestimates the impact of referrals on wages and turnover. Therefore the two sets of estimates are best viewed as *upper* bounds (data-based) and *lower* bounds (model-based) for the true effects of a referral.

5.2 Results Based on Linked PASS-IEB Data

We next present results using the linked PASS-IEB sample which includes direct information on referrals. The upper panel in Table 5 shows the results for wages. As described in detail in Section 4.2, we estimate these models using two alternative methods. First, we use only linked PASS-IEB spells for which we observe whether or not a worker obtained her job through a referral. To control for worker- and firm heterogeneity, we include pre-

population, $\tilde{S}_g = 1.8$ percent, a 10 percentage point increase in the minority share in the firm in the year before the hire thus corresponds to an increase in the probability of having obtained the job through a referral by 26.9 percentage points.

estimated worker and firm fixed effects as control variables to account for the non-random use of referrals (first sub-panel in Panel A). Second, we add to all linked PASS-IEB spells for which we observe whether the worker obtained the job through a referral all other social security records of full-time workers between 2002 and 2012, and jointly estimate the worker and firm fixed effects (results in second sub-panel of Panel A). While both methods lead to very similar point estimates, the latter produces lower standard errors once worker and firm effects are accounted for (columns (3) to (5)). Focusing on column (5) in Panel A which includes pre-estimated (first sub-panel) or jointly estimated (second sub-panel) worker and firm fixed effects and therefore most closely corresponds to our preferred specification in column (5) of Table 4, we find that referrals increase workers' starting wages by around 3.3 percent. This initially positive effect rapidly declines with tenure in the firm at an annual rate of 1.7 percentage points and 2.3 percentage points, respectively.

Panel B in Table 5 shows the corresponding results for turnover. Since monthly information on firm tenure is available only for the spells that are part of the PASS-IEB data but not for the added social security spells, we only report results which include pre-estimated firm and worker fixed effects (corresponding to those in the first sub-panel of Panel A).[34] Focusing again on the results displayed in column (5), we see that having obtained a job through a referral significantly reduces the probability of leaving the firm at the beginning of the employment relationship relative to an external hire by around 1.6 percentage points, or 24.6 percent of the baseline monthly turnover rate of 6.5 percent. Again, this effect rapidly declines with tenure in the firm.[35]

[34]Estimating turnover regressions with fixed effects as in the second sub-panel in A requires using yearly (instead of monthly) turnover information, which leads to a large loss of information because of the short firm tenures in the PASS-IEB sample.

[35]In a sample of workers with low firm tenure, as in the PASS-IEB data, more precise estimates for turnover than for wages are not surprising, since there is a lot more variation in firm tenure than in wages as wages tend to move relatively little from one month to the next, while workers may separate from firms in any month of the year.

5.3 Comparing Matched Employer-Employee and PASS-IEB Estimates

In Table 6, we compare the direct wage and turnover estimates based on the PASS-IEB data (column (3)) with the implied effects of a referral derived from the matched employer-employee data after applying the data-based (column (1)) and model-based (column (2)) transformations (see Section 5.1.3). All three sets of results show qualitatively the same patterns.[36] Quantitatively, the initial increase in wages of 3.3 percent using direct information on referrals is similar to our conservative model-based estimate of 2.5 percent derived from the matched employer-employee data. In contrast, the initial decline in turnover, relative to the baseline turnover rate, using direct information on referrals is larger than our model-based (lower bound) estimate of 6.7 percent, and similar to our data-based (upper-bound) estimate of 18.8 percent, obtained from the matched employer-employee data.

Further, relative to the initial wage and turnover effects of referrals, the fade-out of these effects with firm tenure is more pronounced in the PASS-IEB data than in the matched employer-employee data. For instance, in the matched employer-employee data, the ratio of the estimated initial effect of referrals on wages and (the absolute value of) the estimated annual decline of this effect is 3.3, compared to 1.9 in the PASS-IEB data. This suggests faster learning in the PASS-IEB data, which is not surprising given the typically low complexity of the types of employment this sample represents and the short median firm tenure of only 0.75 years versus between 2 and 3 years in the matched employer-employee data.

Overall, the combined evidence from the large-scale matched employer-employee data and the smaller linked PASS-IEB data provide strong evidence that referrals lead to better matches and that, due to fast learning about match quality, these effects rapidly decline with tenure in the firm.

[36]Note that the computed standard errors reported in Table 6 suggest that the individual point estimates across the three sets of results are statistically not significantly different from each other.

5.4 The Welfare Gain of Referrals

In the final step of the empirical analysis, we quantify by how much referrals reduce uncertainty about workers' productivity and by how much they increase welfare, through noise reduction and better matches.

We base our calculations on our most conservative estimates based on the large-scale matched employer-employee data, exploiting the structure of our model to transform estimates of the share of workers from the own minority group in the firm prior to the hire into estimates of referrals. The estimates in column (5) of Table 4 in Panel C imply that a referral raises wages in a worker's first year at the firm by 2.6 percent, and wages in subsequent years by 0.4 percent.[37] These model-based estimates are lower than those we would obtain using the data-based transformation of the own share effects into referral effects as well as those that are directly estimated from the linked PASS-IEB data, so that the welfare effects we report below may be viewed as a lower bound.

In addition to the noise of the productivity signal in the referral market, σ_R^2, the key parameter that governs the welfare gain of referrals is the learning rate, α: information about the job applicant prior to the hire is the more valuable the slower agents learn. To illustrate the potential welfare gains due to referrals, we uncover these two parameters exploiting the structure of our model. We do that by matching two key data moments, the difference between the log wage of referral and external hires at the beginning of the employment relationship ($\Delta \ln w_{Entry}^{Data} = 0.026$) and the difference between the log wage of referral and external hires in subsequent years of the employment relationship ($\Delta \ln w_{Subsequent}^{Data} = 0.004$), to their model equivalents. The model equivalents $\Delta \ln w_{Entry}^{Model}$ and $\Delta \ln w_{Subsequent}^{Model}$ are given by equations (A-11) and (A-13) in Appendix A.5. Both are complicated functions of α and σ_R^2. In our model, the lower σ_R^2 (relative to σ_E^2), the larger $\Delta \ln w_{Entry}^{Model}$. Moreover, the higher α, the lower $\Delta \ln w_{Subsequent}^{Model}$.

We compute these model moments over a fine grid of values for α and σ_R^2, for given values of the other parameters in our model. We then pick those values for α and σ_R^2 that

[37] We use the empirical wage results for entrants and incumbents reported in Panel C of Table 4 since we can derive analytical expressions for these moments from our model, greatly facilitating the subsequent welfare calculations.

minimize the sum of the squared distance between the model and the data moments:

$$\min_{\alpha,\sigma_R^2} [(\Delta \ln w^{Model}_{Subsequent}(\alpha,\sigma_R^2) - \Delta \ln w^{Data}_{Subsequent})^2 + (\Delta \ln w^{Model}_{Entry}(\alpha,\sigma_R^2) - \Delta \ln w^{Data}_{Entry})^2].$$

We describe the values of the other parameters as well as details of the calibration in Appendix A.5. Assuming a value of 0.5 for the bargaining power (γ) of the workers, the results from the simulation of the model yield $\sigma_R^2 = 0.62$ (standard error 0.04) and $\alpha = 0.50$ (0.12), implying that referrals reduce the uncertainty about the worker's productivity by 41.4 percent relative to the external market and that the true productivity of the worker is revealed with a 50 percent probability in any given period.

To assess the welfare gain that arises from the noise reduction in the referral market and the better matches of the workers with their firms, we re-solve the model and calculate overall welfare, given by the value of being unemployed, assuming that the uncertainty in the referral market is the same as in the external market, $\sigma_R^2 = \sigma_E^2$. Our findings suggest that welfare increases by 0.62 percent as a result of the better matches produced through the referral market, with a standard deviation of 0.15 percent.[38] While these numbers have to be interpreted with caution, they do suggest that the welfare gains from the noise reduction due to referrals may be non-negligible.

6 Conclusion

In this paper, we propose novel empirical implications of referral-based job search networks, which we derive from a theoretical search model that encompasses both uncertainty in the labor market and the possibility of hiring either through formal channels or through the network. In our model framework, referrals reduce uncertainty about the match-specific productivity of workers and firms. As a result, new workers hired through referrals are, on average, better matched to their firms than workers hired through the external market. However, as workers and firms learn about their match-specific pro-

[38]Assuming asymptotic normality, we simulate the welfare gain for 10,000 joint draws of α and σ_R^2 to obtain an estimate of its standard deviation. The 5th-95th percentile interval of the resulting distribution ranges from 0.42 percent to 0.92 percent.

ductivity, bad matches are terminated and the wage and turnover advantage of referred workers dissipates over time.

Using both large-scale matched employer-employee data that cover all workers and firms in one large West German metropolitan area and unique linked survey-social security data, we find strong support for the predictions of our model: we show that, once we account for the non-random sorting of workers into firms, referrals—proxied as the share of workers from the own minority group in the firm at the time of the hire in the large-scale matched employer-employee data but directly observed in the linked survey-social security data—raise wages and reduce turnover. These effects are particularly strong at the beginning of the employment relationship and quickly decline with tenure in the firm, suggesting that learning about match quality is fast. According to our most conservative estimates, we calculate that total welfare in the economy increases by 0.62 percent as a result of the additional information provided to employers.

In conclusion, we see these findings as strong evidence for the hypothesis that, through referrals, job search networks help to reduce informational deficiencies in the labor market and lead to productivity gains for workers and firms.

Appendix A: Theory

A. 1 Value Functions

The value of the match for referred workers

The worker's value of the job, given that she was referred to the employer, equals:

$$W_{1,R} = w_R + \beta(1-\alpha)(1-\delta)W_{1,R} + \beta\alpha(1-\delta)\int \max(W_2, U)dF_R(y|m_R, \sigma_R^2) + \beta\delta U. \quad \text{(A-1)}$$

The firm's value of the match can be similarly derived as:

$$J_{1,R} = m_R - w_R + \beta(1-\alpha)(1-\delta)J_{1,R} + \beta\alpha(1-\delta)\int \max(J_2, 0)dF_R(y|m_R, \sigma_R^2). \quad \text{(A-2)}$$

Wages are determined by Nash bargaining:

$$W_{1,R} - U = \gamma(W_{1,R} - U + J_{1,R}). \quad \text{(A-3)}$$

The value of unemployment and a vacancy

This period, workers receive the unemployment benefit b. Next period, they obtain a referral offer with probability λ_R^W, and can choose between $W_{1,R}$ and U. Workers who did not receive a referral offer meet a firm in the external market with probability λ_E^W, and can choose between $W_{1,E}$ and U. With probability $(1-\lambda_R^W)(1-\lambda_E^W)$, workers receive neither a referral nor an external offer and remain unemployed. The value of being unemployed therefore equals

$$\begin{aligned} U &= b + \beta\lambda_R^W E\max(W_{1,R}, U) + \beta(1-\lambda_R^W)\lambda_E^W E\max(W_{1,E}, U) \\ &\quad + \beta(1-\lambda_R^W)(1-\lambda_E^W)U. \end{aligned} \quad \text{(A-4)}$$

The value of a vacancy can be similarly derived as

$$\begin{aligned} V &= -k + \beta\lambda_R^F E\max(J_{1,R}, V) + \beta(1-\lambda_R^F)\lambda_E^F E\max(J_{1,E}, V) \\ &\quad + \beta(1-\lambda_R^F)(1-\lambda_E^F)V, \end{aligned}$$

where k is the vacancy cost, λ_R^F is the probability that a worker is referred to the firm, and λ_E^F is the probability that a firm meets a job seeker in the external market. Since the free entry condition implies V=0, we have

$$k = \beta\lambda_R^F E\max(J_{1,R}, 0) + \beta(1-\lambda_R^F)\lambda_E^F E\max(J_{1,E}, 0). \quad \text{(A-5)}$$

The probability that a firm meets a worker through the referral market is equal to the probability that the connection of the chosen employee is unemployed. Hence, in steady-state, $\lambda_R^F = u$. The following conditions need to hold for a worker to obtain a referral offer: Her connection must be employed, work in a firm with a vacancy, and must be picked to make a referral. Let v denote the steady-state vacancy rate. A firm with P_j positions will have $P_j v$ vacancies and employ $P_j(1-v)$ workers, on average. Hence, the probability that a particular worker in the firm is asked to make a referral is $v/(1-v)$, and $\lambda_R^W = (1-u)v/(1-v)$.[39] The probabilities that a firm meets a worker and that a worker meets a firm in the external market are $\lambda_E^F = m(u_E, v_E)/v_E$ and $\lambda_E^W = m(u_E, v_E)/u_E$, where $u_E = u(1-\lambda_R^W)$ and $v_E = v(1-\lambda_R^F)$.

A. 2 Reservation Match Qualities and Empirical Implications

We begin with computing y^*, the reservation match quality after the worker's true productivity has been revealed. We then derive the reservation expected match quality for unemployed workers who are hired through the referral and external market (m_R^*, m_E^*). We finally show that referral hires initially earn higher wages and are less likely to leave the firm, but that these effects decline with tenure.

Reservation Match Quality for Employed Workers Workers stay with the firm if the total surplus of the match, $S_2 = W_2 - U + J_2$, is positive. Rearranging W_2 and J_2 (see Section 2.2) and adding them up yields:

$$S_2 = \frac{y - (1-\beta)U}{1-\beta(1-\delta)}.$$

Hence, the reservation match quality y^* equals:

$$y^* = (1-\beta)U,$$

regardless of whether the worker was hired through the referral or external market.

Reservation Match Quality for Unemployed Workers Next, we derive an expression for the reservation expected match quality in the referral and external market, m_R^* and m_E^*. The worker accepts the wage offer if the total surplus of the match, $S_{1,i} = W_{1,i} - U + J_{1,i}$, $i = R, E$, is positive. Rearranging $W_{1,i}$ and $J_{1,i}, i = R, E$ (see Section 2.2 and equations(A-1) and (A-2)), adding them up, and using $y^* = (1-\beta)U$, yields:

$$S_{1,i} = \frac{m_i + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty} (y - y^*) dF_i(y|m_i, \sigma_i^2) - y^*}{1 - \beta(1-\alpha)(1-\delta)}.$$

[39] Here, we have assumed that the number of workers that the firm employs always exceeds the number of vacancies in the firm. For a vacancy rate of 10 percent, the probability that a firm with 10 positions has at least 6 vacancies is less than 0.015 percent.

Hence,

$$m_i^* = y^* - \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty} (y - y^*) dF_i(y|m_i^*, \sigma_i^2). \tag{A-6}$$

The last term is a positive function of σ_i^2, the noise of the productivity signal. Hence, $m_R^* > m_E^*$.

Referral versus External Hires: Wages Using the sharing rule (A-3), referral and external hires whose productivity has not yet been revealed earn a wage equal to:

$$\begin{aligned} \overline{w}_i &= \int_{m_i^*}^{\infty} w_i dG_i(m_i) \Big/ (1 - G_i(m_i^*)) \\ &= \gamma \int_{m_i^*}^{\infty} m_i dG_i(m_i) \Big/ (1 - G_i(m_i^*)) + (1-\beta)(1-\gamma)U, i = R, E. \end{aligned} \tag{A-7}$$

Since $m_R^* > m_E^*$, $\overline{w}_R > \overline{w}_E$.

Making use of sharing rule $W_2 - U = \gamma(W_2 - U + J_2)$, referral and external hires whose productivity has been revealed and who continue to stay with the firm earn a wage equal to:

$$\begin{aligned} \overline{w}_{2,i} &= \int_{m_i^*}^{\infty} \frac{\int_{y^*}^{\infty} w_2 dF_i(y|m_i, \sigma_i^2)}{1 - F_i(y^*|m_i, \sigma_i^2)} dG_i(m_i) \Big/ (1 - G_i(m_i^*)) \\ &= \gamma \int_{m_i^*}^{\infty} \frac{\int_{y^*}^{\infty} y dF_i(y|m_i, \sigma_i^2)}{1 - F_i(y^*|m_i, \sigma_i^2)} dG_i(m_i) \Big/ (1 - G_i(m_i^*)) \\ &\quad + (1-\beta)(1-\gamma)U, i = R, E. \end{aligned} \tag{A-8}$$

It is straightforward to show that $\overline{w}_{2,i} > \overline{w}_i$; hence, wages of workers who stay with their firm increase on average. Numerical simulations show that $\log \overline{w}_{2,E} - \log \overline{w}_E > \log \overline{w}_{2,R} - \log \overline{w}_R$. Hence, referral hires initially earn higher wages than external hires, but their wage advantage declines with tenure.

Referral versus External Hires: Turnover The probability that a worker whose productivity has not been revealed yet leaves the firm in the next period equals

$$\Pr(\text{move}|i = R, E) = \delta + \frac{\alpha(1-\delta) \int_{m_i^*}^{\infty} \int_{-\infty}^{y^*} dF_i(y|m_i, \sigma_i^2) dG_i(m_i)}{\int_{m_i^*}^{\infty} dG_i(m_i)}.$$

Numerical simulations show that Pr(move|i=E) > Pr(move|i=R). Hence, external hires are initially, at the beginning of the employment relationship, more likely to leave the firm than referral hires.

The probability that a worker whose productivity has already been revealed leaves the firm in the next period equals δ, the exogenous job destruction rate, and is the same for referral and external hires. The difference between the turnover rate of referral and external hires therefore declines with tenure.

A. 3 Steady State Unemployment and Vacancy Rate

The number of workers obtaining a job in each period equals:

$$\begin{aligned} \text{outflow unemployment} &= Nu\lambda_R^W(1-G_R(m_R^*)) + Nu(1-\lambda_R^W)\lambda_E^W(1-G_E(m_E^*)) \\ &:= N_{0,R} + N_{0,E}, \end{aligned} \tag{A-9}$$

where $G_i(.), i = R, E$, denotes the distribution from which expected match qualities are drawn.[40]

Turning to the inflow into unemployment, each period $N(1-u)\delta$ workers lose their job for exogenous reasons. Only workers whose productivity is unknown are at risk of leaving the firm for endogenous reasons. An endogenous separation occurs if workers did not lose their job for exogenous reasons $(1-\delta)$, their productivity becomes known (α) this period, and turns out to be below the reservation match quality y^*. After T periods with the firm, there are $(1-\alpha)^T(1-\delta)^T(N_{0,R}+N_{0,E})$ workers whose productivity has not been revealed yet. Hence, the total number of workers becoming unemployed in each period equals:

$$\text{inflow unemployment} = N\delta(1-u) + \sum_{i=R,E} \frac{\alpha(1-\delta)\int_{m_i^*}^{\infty}\int_{-\infty}^{y^*} dF_i(y|m_i,\sigma_i^2)dG_i(m_i)/(1-G_i(m_i^*))}{1-(1-\alpha)(1-\delta)} N_{0,i}. \tag{A-10}$$

A. 4 Alternative Network Structures

More than one connection Our model assumes that workers are connected to only one worker. Next, we show that the implications of our model also hold if workers are connected to more than one worker.[41] In this case, the probability that a minority

[40] G_i is normally distributed with mean μ and variance $\frac{\sigma_\mu^4}{\sigma_\mu^2+\sigma_i^2}, i = R, E$.

[41] We have abstracted from this possibility because workers may end up with more than one referral job offer in the same period. Hence, workers do not necessarily accept a wage offer if it exceeds the value of unemployment.

worker obtained her job through a referral becomes:

$$\Pr(\text{Referral}|\text{Hire}_j^\tau = \text{Minority}) = \frac{S_{\text{Min}j}^{\tau-1}\tilde{u}\Pr(m > m_R^*)}{S_{\text{Min}j}^{\tau-1}\tilde{u}\Pr(m > m_R^*) + S(1-\tilde{u})\lambda_E^F \Pr(m > m_E^*)},$$

where $\tilde{u}$ is the probability that at least one network member is unemployed.[42] As in the model with one connection, a higher share of minority workers in the firm increases the probability that a minority worker obtained her job through a referral. Moreover, the probability that a minority worker is hired continues to depend positively on the existing share of minority workers in the firm:

$$\Pr(\text{Hire}_j^\tau = \text{Minority}) = \frac{S_{\text{Min}j}^{\tau-1}\tilde{u}\Pr(m > m_R^*) + S(1-\tilde{u})\lambda_E^F \Pr(m > m_E^*)}{\tilde{u}\Pr(m > m_R^*) + (1-\tilde{u})\lambda_E^F \Pr(m > m_E^*)}.$$

More than one minority group and partially ethnicity-based networks Next, suppose instead that there is more than one minority group, and that minority workers are not only connected with minority workers from their own group, but also with minority workers from other groups or with majority workers. The probability that a minority worker from group g was hired through a referral is:

$$\Pr(\text{Referral}|\text{Hire}_j^\tau = \text{Minority}_g) = \frac{(S_{gj}^{\tau-1}(\gamma_{gg}-\gamma_{Gg}) + \sum_{g'\neq g} S_{g'j}^{\tau-1}(\gamma_{g'g}-\gamma_{Gg}) + \gamma_{Gg})u\Pr(m > m_R^*)}{\begin{array}{r}[(S_{gj}^{\tau-1}(\gamma_{gg}-\gamma_{Gg}) + \sum_{g'\neq g} S_{g'j}^{\tau-1}(\gamma_{g'g}-\gamma_{Gg}) + \gamma_{Gg})u\Pr(m > m_R^*) \\ + S_g(1-u)\lambda_E^F\Pr(m > m_E^*)]\end{array}}.$$

Here, $\gamma_{g'g}$ (γ_{Gg}) is the probability that a minority worker from group g' (a German worker) is connected to a minority worker from group g. Hence, a higher share of workers from the own minority group increases the probability of a referral hire as long as a minority worker is more likely to be connected to a worker from her own group than a German worker is, $\gamma_{gg} > \gamma_{Gg}$. This assumption also implies that a higher share of workers from the own minority group positively affects the probability that the firm hires from that group:

$$\Pr(\text{Hire}_j^\tau = \text{Minority}_g) = \frac{\begin{array}{r}[(S_{gj}^{\tau-1}(\gamma_{gg}-\gamma_{Gg}) + \sum_{g'\neq g} S_{g'j}^{\tau-1}(\gamma_{g'g}-\gamma_{Gg}) + \gamma_{Gg})u\Pr(m > m_R^*) \\ + S_g(1-u)\lambda_E^F\Pr(m > m_E^*)]\end{array}}{u\Pr(m > m_R^*) + (1-u)\lambda_E^F\Pr(m > m_E^*)}.$$

[42]For simplicity, we have assumed that in case a worker knows more than one unemployed worker, she randomly refers one of them to her employer. If instead she refers the more productive worker (i.e. the one with the higher signal), there is an additional reason for why referral hires are better matched with their firm than external hires.

A. 5 Calibration

The difference between the log wage of referral and external hires at the beginning of the employment relationship in our model is given by:

$$\Delta \ln w^{Model}_{Entry} = \ln \overline{w}_R - \ln \overline{w}_E, \tag{A-11}$$

where $\overline{w}_R$ and $\overline{w}_E$ are given by equation (A-7). The mean wage in subsequent years of the employment relationship is a weighted average of the wage of workers whose productivity has not been revealed yet, $\overline{w}_i$, $i = R, E$, and that of workers whose productivity is known, $\overline{w}_{2,i}$, given by equation (A-8). Let $\overline{w}_{sub,i}$, $i = R, E$, denote this mean wage for workers who have been hired through the external or referral market, respectively. $\overline{w}_{sub,i}$ is given by

$$\overline{w}_{sub,i} = \frac{(1-\alpha)\overline{w}_i + \frac{\alpha}{\delta}\int\limits_{m_i^*}^{\infty}(\int\limits_{y^*}^{\infty} dF_i)dG_i / \int\limits_{m_i^*}^{\infty} dG_i \overline{w}_{2,i}}{(1-\alpha) + \frac{\alpha}{\delta}\int\limits_{m_i^*}^{\infty}(\int\limits_{y^*}^{\infty} dF_i)dG_i / \int\limits_{m_i^*}^{\infty} dG_i}, \qquad i = R, E. \tag{A-12}$$

The difference between the log mean wage of referral and external hires in subsequent years of the employment relationship equals

$$\Delta \ln w^{Model}_{Subsequent} = \ln \overline{w}_{sub,R} - \ln \overline{w}_{sub,E}. \tag{A-13}$$

In steady state, the probability that a firm meets a worker in the referral market is $\lambda^F_R = u$, the probability that a worker meets a firm in the referral market is $\lambda^W_R = (1-u)v/(1-v)$, and the probabilities that a firm meets a worker and that a worker meets a firm in the external market are $\lambda^F_E = m(u_E, v_E)/v_E$ and $\lambda^W_E = m(u_E, v_E)/u_E$, respectively, where $u_E = u(1-\lambda^W_R)$ and $v_E = v(1-\lambda^F_R)$. We assume a constant returns to scale matching function $m(u_E, v_E) = u_E^{\rho} v_E^{1-\rho}$ which implies that $\lambda^F_E = (u_E/v_E)\lambda^W_E = (u/v)(1-\lambda^W_R)/(1-\lambda^F_R)\lambda^W_E = (u/v)(1-(1-u)v/(1-v))/(1-u)\lambda^W_E$. The time period in our model is one year.

Table A.4 lists the values of the exogenous parameters in our model. We normalize average productivity (μ) to 1. The initial variance of productivity, σ^2_μ, and the variance of the productivity signal in the external market, σ^2_E, are taken from Nagypál (2007) who estimates these parameters based on a structural model using French data. The unemployment benefit b is set to 0.67, which roughly corresponds to the replacement rate of unemployment benefits. The elasticity with respect to unemployment in the matching function ρ is set to 0.67. The vacancy cost is calibrated to match the average unemployment rate of all dependent employees in Germany between 1990 and 2001 (10.25 percent). The job destruction rate δ is set to 0.108, the annual quit rate of workers who have been in the labor market for more than 10 years. The discount factor β is 0.95. We use three different values for the bargaining power of workers, $\gamma : 0.25, 0.5$, and 0.75, corresponding to the lower and upper range of parameter values commonly used in the literature.

To compute the model moments, we first compute the six endogenous variables $y^*, m_R^*, m_E^*, u, v, \lambda_E^W$ of our model for the parameter values in Table A.4 and a fine grid of values for α and σ_R^2. There are six equations that determine these variables:

1+2) The reservation match quality of unemployed workers in the referral and external market, m_R^* and m_E^*, given by equation (A-6).

3) The reservation match quality of employed workers, y^*. Simplifying the value of unemployment, given by equation (A-4), yields:

$$\begin{aligned} y^* = & \quad (1-\beta)U \\ = & \quad b + \beta\gamma(1-u)v/(1-v) \int_{m_R^*}^{\infty} \left(\frac{m_R - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty}(y-y^*)dF_R(y|m_R,\sigma_R^2)}{1-\beta(1-\alpha)(1-\delta)}\right) dG_R(m_R) + \\ & \beta\gamma(1-(1-u)v/(1-v))\lambda_E^W \int_{m_E^*}^{\infty} \left(\frac{m_E - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty}(y-y^*)dF_E(y|m_E,\sigma_E^2)}{1-\beta(1-\alpha)(1-\delta)}\right) dG_E(m_E). \end{aligned}$$

4) The free entry condition, given by (A-5):

$$\begin{aligned} k = & \quad \beta(1-\gamma)u \int_{m_R^*}^{\infty} \left(\frac{m_R - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty}(y-y^*)dF_R(y|m_R,\sigma_R^2)}{1-\beta(1-\alpha)(1-\delta)}\right) dG_R(m_R) + \\ & \beta(1-\gamma)(u/v)\left(1-\frac{(1-u)v}{(1-v)}\right)\lambda_E^W \int_{m_E^*}^{\infty} \left(\frac{m_E - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty}(y-y^*)dF_E(y|m_E,\sigma_E^2)}{1-\beta(1-\alpha)(1-\delta)}\right) dG_E(m_E). \end{aligned}$$

5) The equality of the outflow out of unemployment, given by equation (A-9), and the inflow into unemployment, given by equation (A-10):

$$\begin{aligned} u\frac{(1-u)v}{(1-v)}(1-G_R(m_R^*)) & + \quad u\left(1-\frac{(1-u)v}{(1-v)}\right)\lambda_E^W(1-G_E(m_E^*)) \\ & = \quad \delta(1-u) + \frac{\alpha(1-\delta)\int_{m_R^*}^{\infty} F_R(y^*|m_R,\sigma_R^2)dG_R(m_R)}{1-(1-\alpha)(1-\delta)} u\frac{(1-u)v}{(1-v)}. \\ & + \quad \frac{\alpha(1-\delta)\int_{m_E^*}^{\infty} F_E(y^*|m_E,\sigma_E^2)dG_E(m_E)}{1-(1-\alpha)(1-\delta)} u\left(1-\frac{(1-u)v}{(1-v)}\right)\lambda_E^W. \end{aligned}$$

6) The matching technology:

$$\begin{aligned} v_E &= (\lambda_E^W)^{1/(1-\rho)} u_E \\ v(1-u) &= (\lambda_E^W)^{1/(1-\rho)} u(1-(1-u)v/(1-v)) \end{aligned}$$

After having solved for these endogenous parameters, we compute for each set of values for α and σ_R^2 the two model moments given by equations (A-11) and (A-13), using again the parameter values in Table A.4. We finally compute the squared distance between the model and data moments, and select those values of α and σ_R^2 that minimize this distance.

Appendix B: Linked Survey-Social Security Data

The key information on referrals has been taken from two different household surveys, which can both be linked to the social security data on individual employment biographies. The first survey is the Panel Study "Labour Market and Social Security" (PASS), a longitudinal study conducted by the Institute for Employment Research (IAB) annually since 2007 (see Trappmann et al., 2013, for details). The PASS survey covers two populations of equal size: the first one is drawn from households registered as residents in Germany and the second one from households with at least one means-tested benefit recipient member. There are six waves of PASS available, with the last wave in the field in 2012, questioning approximately 14,600 persons in 9,500 households. About 12,680 of these persons and 8,400 of these households were surveyed multiple times. In waves 3, 5 and 6, the PASS survey contains a question on the way individuals found their new job(s) during a given pre-interview survey period.[43] We treat the answer that the respondent found her job through relatives or acquaintances as a proxy for a referral. Out of 6,275 persons who answered the job search questions across the different waves, 26 percent found their job through this channel. Note that individuals can have several new job spells within one survey period and, of course, in different waves of the survey, so that for many individuals multiple job spells with job search information are available. The survey information from the PASS is linked via a personal identifier to the social security data of the Integrated Employment Biographies (IEB) if the participants agree to the record linkage. The approval rate is around 80 percent. For our analysis, we only use those employment spells in the PASS survey that we can match exactly to a corresponding spell in the IEB social security data based on the stated starting month and year of the spell.

The second survey is the IAB-SOEP Migration Sample, a new longitudinal study of immigrants in Germany jointly conducted by the IAB and the German Socio-Economic Panel (SOEP) (see Brücker et al., 2014, for details). The first wave of the IAB-SOEP Migration Sample was carried out in 2013 and covers approximately 5,000 first and second generation immigrants living in 2,900 households. For the subsample of first generation immigrants, it contains a question on the way they found their first job in Germany.[44] We treat the answer that the respondent found this job through friends, acquaintances or relatives as a proxy for a referral. Out of the 3,053 respondents who immigrated to

[43] For each of the new jobs started, the exact question and answer categories are: "How did you get notice of this job? (1) Through a newspaper advert (2) Through the online job exchange of the job agency (Agentur für Arbeit) (3) From another online source (4) Through relatives or acquaintances (5) Through an agent at the job agency (6) Through a private agent (7) By asking for a job at a company (8) Open, namely...".

[44] The exact question and answer categories are: "What about before you moved to Germany: How did you find your first job? (1) Through the Federal Employment Agency (Bundesagentur für Arbeit) (2) Through an employment office/agency in my home country (3) Through an employment agency for foreigners (4) Through a private job agency (5) Through a job advertisement in a newspaper (6) Through a job advertisement on the internet (7) Through friends, acquaintances, or relatives (8) Through business relationships in Germany (9) Was self-employed in my first job (10) Have never worked in Germany".

Germany and participated in the labor market, 54 percent found their first job through this channel. Note that in contrast to the PASS survey, the IAB-SOEP Migration Sample comprises only immigrants and that the referral question refers to the first job in Germany rather than the current job. Similar to the PASS-IEB data, the IAB-SOEP Migration Sample links the survey responses to the social security data of the IEB via a personal identifier. Since the IAB-SOEP Migration Sample is based on face-to-face interviews, German data protection regulations require that respondents sign an approval form for the record linkage. Compared to the PASS survey, where only a verbal approval is requested, this reduces the approval rate to slightly above 50 percent in the first wave. Moreover, since a third of the respondents have been excluded from the record linkage question for methodological reasons, we are left with around one-third of the cases for our analysis. To match the job search information to the corresponding employment spell, we use the first employment spell found in the IEB data after the last reported arrival date in Germany reported by the respondent in the survey.

Appendix C: Robustness Checks

In Table A.2, we display findings for the impact of the share of workers from the same minority group in the firm prior to the hire on wages and turnover decisions of minority workers in the three other metropolitan areas, focusing on our main specification shown in column (5) of Panel B in Table 4. With the exception of Cologne, where the wage effects are somewhat larger and the turnover effects somewhat smaller, the impact of the share of workers from the same minority group in the firm at the time of the referral on wages and turnover is very similar in magnitude across regions.

In Table A.3, we show that our baseline findings in Table 4 are robust to a number of alternative specifications. For comparison, column (1) shows our baseline estimate from Table 4, Panel B, column (5), where we condition on fixed worker and fixed firm effects.

In column (2), we include firm-year of hire fixed effects instead of firm fixed effects, thereby allowing for firm-specific time shocks. Identification is now coming from firms employing different minority groups at varying proportions in a given year. The coefficient for the wage effect in the first year increases somewhat in magnitude to 0.089, while the coefficient for the turnover effect in the first year is similar to that in our baseline results. In column (3), we only consider the five main minority groups (the same as in Table 2), and allow all control variables to have a different effect for each minority group.[45] Again, results are similar to our baseline findings. To further control for potential supply side factors, we add the share of minority workers from the same group in the industry and municipality one year before the hire as additional controls in column (4). Like the corresponding shares at the firm level, their effect is allowed to vary between a worker's first year at the firm and a worker's subsequent years at the firm. This has little impact

[45] For computational reasons, this is impossible if we include all 203 minority groups.

on our findings.

Our baseline specification in column (1) includes Germans in the estimation sample (see Section 4.1), and therefore restricts the fixed firm effect to be the same for the minority and German population. In column (5), we estimate equation (2) for minorities only and therefore allow for a minority-specific fixed firm effect. The share of workers from the same minority group in the firm continues to have a positive effect on wages and a negative effect on turnover of those workers who have just entered the firm. As in the baseline specification, both effects decline with tenure. In column (6), we restrict the sample further to minority workers from Germany's guest worker countries Turkey, Greece, Italy, Former Yugoslavia, Spain and Portugal. These workers form a fairly homogenous group: they entered Germany around the same time in the 1960s, and are predominantly low-skilled. Results are similar to those in column (5).

Finally, in column (7), we add the joint share of workers from all other minority groups one year before the worker was hired as an additional control variable in our baseline specification, again to proxy for the more general degree of openness of the firm to non-German workers (compare Table 2, column (3)). As before, this has little effect on our point estimates.

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Table 1: Descriptive Evidence on Referrals and Ethnicity-Based Networks

Panel A: Usage of referrals (in %)	(1)	(2)	(3)
	Obtained job through acquaintances, friends and relatives		
	PASS-IEB	IAB-SOEP	SOEP
Germans	25.3	-	31.0
Minorities			
All	28.7	46.8	42.7
Low-skilled	35.2	53.3	45.1
Medium-skilled	28.3	46.7	40.5
High-skilled	19.6	31.3	37.1

Panel B: Origin of first friend (in %)	First friend is from a minority group	First friend is from same country of origin (conditional)
Germans	4.90	
Minorities		
All	61.7	91.7
Guest workers	69.2	95.1
In Germany for more than 10 years	63.0	93.9
In Germany for at most 10 years	68.9	89.1
German-born	47.8	87.1

Note: Panel A shows the fractions of full-time workers aged 15-64 who obtained their current (PASS-IEB and SOEP) or first (IAB-SOEP) job through family members, acquaintances, or friends. Panel B displays for the sample of dependent employees aged 15-64 the probability that the first befriended person is from a minority group and, for those minority workers whose first befriended person is from a minority group, the probability that this friend is from the same country of origin.
Source: Panel A: PASS-IEB, IAB-SOEP Migration Sample, and SOEP (1990-2001). Panel B: SOEP for 1996 and 2001 (apart from the results for "German-born" which are based on the 2001 wave only).

Table 2: The Share of Workers from the Same Minority Group and the Probability of Getting Hired (5 Largest Minority Groups)

	(1)	(2)	(3)
Own share, τ-1	0.568**	0.498**	0.498**
	(0.016)	(0.015)	(0.015)
Year x minority FE	yes	yes	yes
Additional control variables	no	yes	yes
Share other minority groups, τ-1	no	no	yes
Firms	95,158	95,158	95,158
Observations	2,116,675	2,116,675	2,116,675

Note: The table reports the results from regressing the minority-specific shares of new hires for the 5 largest minority groups (Yugoslavs, Turks, Austrians, Italians, and Greeks) on the corresponding shares of minority workers in the firm in the previous year. Column (1) includes only minority/year fixed effects. Column (2) includes the shares of new hires with low and medium education, the share of new hires that are women, the lagged shares of workers with low and medium education in the firm, and the lagged share of women in the firm. All of these demand side control variables are interacted with minority group dummies. In addition, the regression includes the minority share in the local municipality (222 municipalities), the minority share in the industry of the firm (12 industries), and the predicted minority share based on the occupational composition of the firm (88 occupations) as supply side control variables. The predicted minority share based on the occupational composition of the firm measures the hypothetical minority share of the firm if it hired purely according to its occupational structure, taken as given the existing distribution of minority workers over different occupations. Column (3) additionally controls for the share of workers from other minority groups in the firm in the previous year. Standard errors are clustered at the firm level. Observations are weighted by the number of hires per year.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Matched Employer-Employee Data, Munich.

Table 3: Link Between Referrals and Own Minority Share

	(1)	(2)	(3)	(4)	(5)
		PASS-IEB		IAB-SOEP	
	OLS, no controls	OLS, controls	Worker and firm effects	OLS, no controls	OLS, controls
Own share, τ-1 X minority	1.093*	0.931	0.982*	0.585**	0.550**
	(0.477)	(0.491)	(0.490)	(0.113)	(0.134)
Own share, τ-1 X German	0.106	0.121	0.116		
	(0.173)	(0.175)	(0.175)		
Controls	no	yes	yes	no	yes
Pre-estimated worker and firm FE	no	no	yes	no	no
Observations	750	750	750	404	404

Note: The table reports the impact of the share of workers from the own minority background (country of birth or that of the parents) in the firm one year before the worker was hired on the probability of having obtained the job through a referral. The sample includes full-time workers starting their first ever job in a given firm. In columns (1) and (4), we only control for workers' minority status and year fixed effects. In columns (2) and (5), we control for gender, educational attainment, age and age squared, log firm size, industry fixed effects and year fixed effects. In column (3), we add pre-estimated worker and firm fixed effects calculated using the 6 year window prior to the hiring. In this case, the year fixed effects refer to the time window over which the fixed effects were estimated.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: PASS-IEB (columns 1-3) and IAB-SOEP Migration Sample (columns 4-5).

Table 4: The Impact of the Share of Workers from the Same Minority Group on Wages and Turnover

	(1) OLS, no controls	(2) OLS, controls	(3) Fixed worker effects	(4) Fixed firm effects	(5) Fixed worker and firm effects
Panel A: Average effects					
Wages					
Own share, τ-1	-0.189**	-0.082**	-0.030**	0.052**	0.043**
	(0.005)	(0.004)	(0.006)	(0.009)	(0.006)
Turnover					
Own share, τ-1	0.124**	0.014**	0.039**	-0.056**	-0.022
	(0.003)	(0..003)	(0.009)	(0.006)	(0.012)
Panel B: Tenure interactions					
Wages					
Own share, τ-1	-0.189**	-0.082**	-0.012	0.102**	0.066**
	(0.005)	(0.004)	(0.006)	(0.009)	(0.007)
Own share, τ-1 X tenure	0.005**	-0.0002	-0.015**	-0.018**	-0.020**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Turnover					
Own share, τ-1	0.138**	0.046**	0.011	-0.047**	-0.052**
	(0.003)	(0.004)	(0.009)	(0.008)	(0.014)
Own share, τ-1 X tenure	-0.011**	-0.013**	0.024**	-0.003	0.026**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Panel C: First year versus subsequent years					
Wages					
Own share, τ-1, first year	-0.192**	-0.085**	-0.018*	0.107**	0.069**
	(0.004)	(0.003)	(0.006)	(0.008)	(0.006)
Own share, τ-1, subsequent years	-0.162**	-0.080**	-0.045**	0.020	0.010
	(0.006)	(0.005)	(0.007)	(0.011)	(0.006)
Turnover					
Own share, τ-1, first year	0.151**	0.061**	0.016	-0.058**	-0.064**
	(0.005)	(0.005)	(0.009)	(0.010)	(0.014)
Own share, τ-1, subsequent years	0.080**	-0.016**	0.070**	-0.055**	0.031*
	(0.004)	(0.003)	(0.010)	(0.007)	(0.014)

Note: In Panel A, we report the overall impact of the share of workers from the own minority group in the firm one year before the worker was hired on wages and turnover of minority workers. In Panel B, we allow the impact of the own share to vary by tenure. In Panel C, we allow for a different impact of the share of own-type workers in a worker's first year at the firm and a worker's subsequent years at the firm. In column (1), we control only for the worker's minority status and year fixed effects. In column (2), we add controls for firm and worker characteristics. The covariates are: 5 firm tenure categories (0 years, 1-2 years, 3-4 years, 5-9 years, ≥10 years), the log of the firm size, age, age squared, industry dummies, education dummies and a gender indicator. We then add fixed worker effects (column (3)), fixed firm effects (column (4)), and both fixed worker and firm effects (column (5)). Standard errors are clustered at the worker level in columns (1) to (2), and bootstrapped using 50 repetitions in column (5). The number of observations is 5,757,700 (of which 1,076,425 refer to minority workers) in the wage regressions and 5,246,295 (979,871) in the turnover regressions.

Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Source: Matched Employer-Employee Data, Munich.

Table 5: The Impact of a Referral on Wages and Turnover - PASS-IEB

	(1) OLS, no controls	(2) OLS, controls	(3) Fixed worker effects	(4) Fixed firm effects	(5) Fixed worker and firm effects
Panel A: Wages					
PASS-IEB sample (pre-estimated worker and firm fixed effects)					
Referral	0.021	0.007	0.028	0.016	0.033
	(0.044)	(0.035)	(0.029)	(0.030)	(0.026)
Referral X tenure	-0.028	-0.020	-0.025	-0.012	-0.017
	(0.041)	(0.027)	(0.024)	(0.021)	(0.019)
PASS-IEB sample plus social security records (jointly estimated worker and firm fixed effects)					
Referral	0.000	0.011	0.053*	0.021	0.034*
	(0.028)	(0.026)	(0.021)	(0.019)	(0.015)
Referral X tenure	-0.051	-0.043	-0.046*	-0.027	-0.023*
	(0.036)	(0.032)	(0.014)	(0.018)	(0.010)
Panel B: Turnover (pre-estimated worker and firm fixed effects)					
Full-time workers					
Referral	-0.011	-0.014*	-0.017*	-0.016*	-0.016*
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Referral X tenure	0.009*	0.010*	0.012*	0.012*	0.012*
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)

Note: The table reports the effects of a referral on wages (Panel A) and turnover (Panel B) and allows this effect to vary with tenure at the firm. The estimation samples comprise full-time minority and German workers starting their first ever job in a given firm. In the first set of rows in Panel A and in Panel B, we use only those spells from the PASS-IEB data which can be matched exactly to the social security data and for which the referral status is known. In column (1), we control only for the worker's minority status and year fixed effects. In column (2), we add controls for firm and worker characteristics. The covariates are: a cubic in firm tenure, the log of the firm size, age, age squared, industry dummies, education dummies and a gender indicator. In columns (3) to (5), we add pre-estimated worker and firm fixed effects calculated using the 6 year window prior to the hiring. In these case, the year fixed effects refer to the time window over which the fixed effects were estimated. Standard errors are clustered at the worker level. The number of observations is 11,104 in the wage regressions (671 individuals) and 13,447 in the turnover regressions (820 individuals).

In the second set of rows in Panel A, we add to this sample all available full-time spells from the social security records between 2003 and 2012, refering to the 30th of June, for which we do not know whether the worker relied on her social network. The fixed worker and firm effects are now jointly estimated and we report the difference in coefficients between the two dummy variables "obtained the job through a referral" and "did not obtain the job through a referral", where workers whose referral status is unkown form the base category. In columns (1) to (2), standard errors are clustered at the worker level, and in column (5), they are bootstrapped using 50 repetitions.

Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Source: PASS-IEB and Matched Employer-Employee Data.

Table 6: Summary of Results

	(1) Matched employer-employee data	(2) Matched employer-employee data	(3) Linked PASS-IEB data
Time interval	yearly	yearly	monthly
Link own minority share - referral	data-based	model-based	-
Transformation factor	1.02	0.37	-
Baseline turnover probability (in %)	28.2	28.2	6.5
Wage Effects			
Initial period (in %)	6.7	2.5	3.3
	(3.4)	(0.3)	(2.6)
Speed of convergence (per year, in ppt)	-2.0	-0.7	-1.7
	(1.0)	(0.0)	(1.9)
Turnover Effects			
Initial period (in ppt)	-5.3	-1.9	-1.6
	(3.0)	(0.5)	(0.7)
Speed of convergence (per year, in ppt)	2.6	1.0	1.2
	(1.3)	(0.1)	(0.5)
Initial period (relative to baseline, in %)	-18.8	-6.7	-24.6

Note: The table summarizes the magnitudes of the wage and turnover effects of a referral as implied by the estimates reported in Table 4, Panel B, column (5) (for columns (1) and (2)) and Table 5, column (5) (for column (3)). To translate the effect of a change in the own minority share into the effect of a referral, we use the empirical information on the link between the two variables provided in Table 3, column (3) (for column (1)) and the structure of our theoretical model (for column (2)). See Section 5.1.3 ("Magnitude of Findings") for details. Standard errors are calculated using the delta method.

Table A.1: Minority Composition

	(1)	(2)	(3)
		Survey data linked to social security records	
	Matched employer-employee data (Munich)	PASS-IEB	IAB-SOEP Migration Sample
Former Yugoslavia	28.7	11.6	10.2
Turkey	17.7	10.8	9.8
Italy	7.3	11.9	*
Austria	11.9	12.9	*
Greece	5.6	*	*
Poland	2.1	10.8	8.5
Former Soviet Union	0.7	25.1	12.3
Western Europe (Other)	8.1	*	8.5
Eastern and Central Europe (Other)	6.5	2.3	21.2
Asia	5.7	7.7	9.3
Other	5.6	5.1	*

Note: The table first provides an overview of the main minority groups in our matched employer-employee data for the Munich metropolitan area and the two survey data sets linked to social security records (PASS-IEB and the IAB-SOEP Migration Sample). Entries represent shares (in %) of the overall minority population in each sample. Entries marked with a "*" indicate fewer than 20 observations in the cell where, for data protection reasons, we are not allowed to report the exact share.

Source: Column (1): Matched Employer-Employee Data, Munich. Column (2): PASS-IEB. Column (3): IAB-SOEP Migration Sample.

Table A.2: The Impact of the Share of Workers from the Same Minority Group on Wages and Turnover, Other Cities

	Munich	Frankfurt	Cologne	Hamburg
Wages				
Own share, τ-1	0.066**	0.077**	0.149**	0.070**
	(0.007)	(0.008)	(0.009)	(0.009)
Own share, τ-1 X tenure	-0.020**	-0.029**	-0.042**	-0.026**
	(0.001)	(0.001)	(0.001)	(0.001)
Turnover				
Own share, τ-1	-0.052**	-0.094**	-0.026	-0.080**
	(0.014)	(0.018)	(0.019)	(0.021)
Own share, τ-1 X tenure	0.026**	0.027**	0.015**	0.031**
	(0.001)	(0.001)	(0.001)	(0.002)

Note: The table reports the impact of the share of workers from the own minority group one year before the worker was hired on wages and turnover decisions of minority workers, for the four largest West German metropolitan areas. The effect is allowed to vary by tenure. Regressions control for tenure, age and age squared, firm size, and year fixed effects, and include fixed worker and firm effects. See Table 4, Panel B, column (5).
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Matched Employer-Employee Data, Munich, Frankfurt, Cologne and Hamburg.

Table A.3: The Impact of the Share of Workers from the Same Minority Group on Wages and Turnover: Robustness Checks

	(1) Baseline	(2) Fixed firm-year effects	(3) 5 main groups	(4) Plus shares ind. and mun.	(5) Minority workers only	(6) Guest workers only	(7) Plus other share, τ-1
Wages							
Own share, τ-1	0.066**	0.089**	0.062**	0.065**	0.042**	0.043**	0.056**
	(0.007)	(0.009)	(0.007)	(0.006)	(0.006)	(0.009)	(0.006)
Own share, τ-1 X tenure	-0.020**	-0.022**	-0.018**	-0.024**	-0.019**	-0.021**	-0.019**
	(0.001)	(0.001)	(0.006)	(0.006)	(0.001)	(0.001)	(0.000)
Observations	5,757,700	5,757,700	5,450,903	5,757,700	1,076,425	715,084	5,757,700
Turnover							
Own share, τ-1	-0.052**	-0.047**	-0.055**	-0.046**	-0.038*	-0.020	-0.051**
	(0.014)	(0.018)	(0.013)	(0.012)	(0.017)	(0.022)	(0.001)
Own share, τ-1 X tenure	0.026**	0.030**	0.028**	0.022**	0.021**	0.016**	0.025**
	(0.001)	(0.001)	(0.001)	(0.015)	(0.001)	(0.002)	(0.001)
Observations	5,246,295	5,246,295	4,974,444	5,246,295	979,871	654,452	5,246,295

Note: The table presents several robustness checks on the impact of the share of workers from the same minority group one year before the worker was hired on wages of minority workers. The effect is allowed to vary by tenure. For comparison, we first display our baseline results from Table 4, Panel B, column (5), in column (1). In column (2), we allow for a fixed firm-year effect. In column (3), we consider only the 5 main minority groups, and allow all control variables to vary for each of the 5 minority groups. In column (4), we add the share of minority workers from the same group in the industry and municipality one year before the worker was hired as additional controls. Like the corresponding share at the firm level, their effect is allowed to vary by tenure. In column (5), we return to the specification of column (1) but restrict the sample to minority workers, and thus allow the fixed firm effect to vary by minority status. In column (6), we further restrict the sample to minority workers from guest worker countries (Turkey, Greece, Italy, Former Yugoslavia, Spain, and Portugal). In column (7), we additionally control for the share of workers from other minority groups one year before the worker was hired. All regressions include worker and firm fixed effects. Standard errors are bootstrapped using 50 repetitions.

Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Source: Matched Employer-Employee Data, Munich.

Table A.4: Parameter Values

Mean productivity	μ	1	normalization
Variance productivity	σ^2_μ	0.3920	Nagypal (2007)
Variance signal, external market	σ^2_E	1.0574	Nagypal (2007)
Unemployment benefit	b	0.670	
Matching	ρ	0.670	Mortensen and Nagypal (2007)
Vacancy cost	k	calibrated	calibrated to match steady state unemployment rate (10.25%)
Job destruction rate	δ	0.108	annual quit rate after 10 years in labor market
Discount factor	β	0.95	
Bargaining power, workers	γ	0.25, 0.5, 0.75	

Note: The table reports the values of the model parameters used in the calibration.