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Non-Technical Abstract

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Keywords: Networks, Referrals, Uncertainty

JEL Classification: J61, J63, J31

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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.[2] 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.

One way how information can be exchanged within networks is among potential employees, by informing each other about job opportunities (see, for example, models by Topa, 2001, and Calvó-Armengol and Jackson, 2004, 2007). In this paper, we focus on an alternative 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 (see also the referral models by Montgomery, 1991, Simon and Warner, 1992, and, more recently, Galenianos, 2011). Based on a theoretical search model that encompasses both uncertainty in the labor market and the possibility of hiring through formal channels or through the network, we propose novel empirical implications of referral-based job search networks. We test these implications using unique matched employer-employee social security data, covering all workers and firms in one large German metropolitan area over a 20 year period. Similar to Borjas (1992, 1995), Bertrand et al. (2000), and Bandiera et al. (2009), we define networks to operate along ethnic minority-group dimensions.[3]

Our model builds on the learning-matching model by Jovanovic (1979, 1984). We extend his analysis by distinguishing between recruitment through networks and through the external market, and by endogenizing the probability of obtaining a job through

[2]See, for instance, Granovetter (1974, 1995), Corcoran et al. (1980), Holzer (1988), Gregg and Wadsworth (1996), and Addison and Portugal (2002).

[3]Evidence from the German Socio-Economic Panel (GSOEP) supports the importance of ethnicity-based networks in the German labor market. For the year 2001, 62.3% (55.7%) of the 2,037 non-German citizens in the sample cite as their first (third) befriended person someone who is also a foreign citizen, compared to only 4.2% (3.9%) of the German citizens in the sample. Of those 62.3%, 92.4% (90.3%) cite as their first (third) befriended person someone who comes from the same country of origin.

a referral and relating it to the workforce composition of the firm. The key difference between the referral and external market is that the worker's match-specific productivity is more uncertain in the external than in the referral market. The model implies that a firm is more likely to hire a minority worker from a particular group, rather than a majority worker or a worker from another minority group, if the share of existing minority workers from that group in the firm is higher. This is because the likelihood that a minority worker from that group is picked to make a referral is increasing in this share. We find strong support of this prediction, even after controlling for observable worker and firm characteristics and detailed measures of the supply of minority workers.

Our model further predicts that workers who have obtained their job through a referral earn initially, at the beginning of the employment relationship, higher wages, and are less likely to leave their firm, than workers who were hired through the external market. However, the model also predicts that both the wage and the turnover advantage of referral hires declines with tenure in the firm. This is because a larger uncertainty of the worker's productivity implies a larger opportunity for future wage growth, as workers are partially insured against low realizations of their productivity by becoming unemployed (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. However, 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.

In our data, we do not directly observe whether a worker obtained his job through the external or the referral market. However, according to our model, the probability of a referral hire is increasing in the share of workers from the same ethnic group in the firm at the time of the hire, which is why we use this share as a proxy for a referral hire. As predicted, we find that, once we control for the non-random sorting of workers into firms, minority workers initially earn higher wages, but experience slower wage growth, if the share of minority workers of the own group one period before the worker was hired is higher. Furthermore, a higher share of workers of the own minority group in the firm at the time of the referral initially lowers turnover of minority workers, but this effect also declines with tenure in the firm. Our baseline findings indicate that a 10 percentage point increase in the share of workers from the own minority group in the firm prior to the hire increases wages in the first year at the firm by 0.68%, and wages in subsequent years by, on average, 0.10%. At the same time, such a 10 percentage point increase implies that the worker is 21.9 percentage points more likely to have obtained his job through a referral. Assuming linearity, a referral thus raises wages of workers in their first year at the firm by 3.1%, and wages in subsequent years by 0.5%. These wage effects are stronger for young and low-skilled workers who have the most to gain from a referral.

Using the structure of our model, we finally compute that uncertainty in the referral market is 46.8% lower than in the external market, and that referrals, through the provision of additional information to employers, increase total welfare in the economy by 0.75%. Overall, our findings 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 firms and workers.

Our paper is most closely 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 of the literature). Granovetter (1974) was one of the first to document the widespread use of friends and relatives in the job search process. The existing evidence on how such use affects 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.[4] Loury (2006) offers a potential explanation,

[4]Kugler (2003) also finds positive returns to employee referrals, although these disappear once the sector of employment is controlled for. Patel and Vella (2007) provide evidence that new arrivals of immigrants choose the same occupations as their countrymen, and that this occupational choice is positively associated with their earnings. Holzer (1987), in contrast, finds no positive wage effects. Loury (2006) emphasizes the importance of the type of job contact, showing that workers who find their job through a referral of high-wage-offer contacts – in her analysis prior generation male relatives – earn more initially but experience slower wage growth than workers who find their job through either low-wage-offer contacts or formal methods. Pellizzari (2010) provides an overview of wage differentials

arguing that depending on their quality, social contacts can either lead to longer job tenure and high wages because they indicate better matches or to longer job tenure and low wages because they indicate a worker's limited range of job alternatives. A key concern in this literature is that 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 identify the causal impact of referrals on wages and turnover under much weaker assumptions than in the existing literature: we eliminate any bias due to the fact that low productivity workers and firms may use networks in their job search process more or less intensively than high productivity workers and firms.

Similar to us, recent research by Bayer et al. (2008) and Hellerstein et al. (2008) does not rely on survey evidence on job search methods to test for the existence of job search networks, but investigates instead whether network members cluster together in the same work-location or firm. These papers define networks locally, as individuals living very closely together. Kramarz and Nordström Skans (2007), on the other hand, focus on the importance of *family*-based networks during the transition from school to work, and analyze whether firms are more likely to hire children of current employees than otherwise comparable job market candidates. Oyer and Schaefer (2009), in turn, look at networks formed by attending the same educational institution. Specifically, they analyze how graduates of law schools group into law firms and find evidence that partners hire graduates from their own law school with a much higher probability than randomization would predict. In a similar spirit, Giuliano et al. (2009) and Åslund et al. (2009a) show that the race or immigrant status of managers affects the racial or immigrant composition of new hires, using data from one large U.S. retail firm and Swedish social security data, respectively. We complement these studies by analyzing ethnicity-based networks, defined as individuals of the same ethnic group living in a large metropolitan area. We go beyond these papers by presenting novel evidence on the productivity of networks, and by providing a theoretical framework that allows us to

between jobs found through informal and formal methods in a number of European countries.

interpret our findings in a concise manner.

Four 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 we do. Schmutte (2009) 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. In this paper, the definition of networks is based on geographic proximity and their effect on wages is identified in a similar way as in Bayer et al. (2008). In Goel and Lang (2009), networks affect wages through the arrival rate of job offers. The key finding is that among strongly connected workers, workers who have obtained their job through formal channels earn higher wages than workers who obtained their job through networks – the reason being that these workers are likely to have received two job offers from which to choose, one through the network and an alternative one through formal channels. Using Canadian survey data on both the strength of an individual's networks and the job finding method, they find empirical support for this prediction. Bandiera et al. (2009) investigate the effect of social connections between workers and managers on productivity, and relate this to the incentive scheme under which managers act. Using data obtained from a unique field experiment, they find that managers favor workers with whom they are socially connected irrespective of the worker's ability if they are paid a fixed wage, but not if their wage depends on workers' average productivities. In line with that, Beaman and Magruder (2010) show that workers whose pay depends directly on the subsequent performance of their referrals are more likely to refer co-workers and less likely to refer relatives to their employer.

Our paper is also related to the literature on ethnic segregation. While most of this literature has focused on residential segregation[5], a few recent papers analyze *firm*-level segregation (see, for example, Carrington and Troske, 1998, as well as the series of papers by Hellerstein and Neumark, 2003, 2008, and Hellerstein et al., 2007, for the U.S., and Åslund and Nordström Skans, 2009b, for Sweden). While these papers compute measures

[5]Studies that analyze ethnic segregation at the residential level include Musterd (2005), Cutler et al. (2008), and Semyonov and Glikman (2009).

of segregation to test for the clustering of minority workers in the same firms, we instead investigate how the firm's existing workforce affects its hiring behavior. Unlike these papers, we focus on a particular mechanism behind ethnic segregation at the firm level, referral-based job search networks, and provide evidence on the benefits of such networks.

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. We describe the data and provide an overview of the main ethnic minority groups in Germany in Section 3. We then explain our empirical methods in Section 4, and report results in Section 5. We discuss the implications of our findings in Section 6, and conclude in Section 7.

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.[6] Our model builds on the learning model by Jovanovic (1979, 1984). We extend his 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

[6] See also Simon and Warner (1992). Pinkston (2008) provides empirical evidence that is consistent with this hypothesis.

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 his expected productivity is m^i.[7]

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 also Appendix A.4). The assumption required is that minority workers are more likely to be connected to other minority workers than German workers are. There is strong evidence in favor of this assumption, see footnote 3.

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 he is employed, the firm hires through the external market.[8]

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

[8]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

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 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, he 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

the external market.

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 0. 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 $W_2(y^*) - U = J_2(y^*) = 0$. Notice 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 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 $W_1^E(m_E^*) - U = J_1^E(m_E^*) = 0$.

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. There is a reservation 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 $W_1^R(m_R^*) - U = J_1^R(m_R^*) = 0$.

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 is constant over time. Equations (A-6) and (A-7) in Appendix A.2 show the outflow out of and inflow into unemployment in each period.

2.3 Empirical Implications

2.3.1 Persistence of Minority Hiring

A key implication of our model is that there is persistence in the share of minority workers in a given workplace. To see this, consider a firm with one vacancy in period $\tau - 1$ that is filled in period τ. Suppose that the share of minority workers in this firm in $\tau - 1$ is $S_{\text{Min}j}^{\tau-1}$. Using Bayes' law, the probability that a minority worker, as opposed to a majority worker, is hired equals:

$$\Pr(\text{Hire=Minority}) = \frac{S_{\text{Min}j}^{\tau-1} u \Pr(m > m_R^*) + S(1-u)\lambda_F^E \Pr(m > m_E^*)}{u \Pr(m > m_R^*) + (1-u)\lambda_F^E \Pr(m > m_E^*)}, \tag{1}$$

where u denotes the steady-state unemployment rate and λ_F^E the probability that the firm meets a worker through the external market. The denominator of the right-hand side of equation (1) is the overall probability that a worker, whether minority or not, is hired, either through the referral or the external market.[9] The numerator is the probability that a minority worker is hired, with S denoting the overall share of minority workers in the population.

[9] The probability that a referred worker is recruited is equal to the probability that the connection of 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_F^E, and the probability that the worker's expected productivity exceeds the reservation match quality, m_E^*.

The probability that the position is filled with a minority worker, rather than a majority worker, is increasing in the share of existing minority workers in the firm, $S^{\tau-1}_{\mathrm{Min}j}$. This is because the likelihood that a minority worker is picked to make a referral is increasing in this share. We begin the first part of our empirical analysis by investigating the relationship between the firm's past workforce composition and the composition of new hires, as shown in equation (1). We describe our empirical strategy in Section 4.1, and report results in Section 5.1.

Note that our model predicts persistence in the share of minority workers in a given firm regardless of whether networks help to reduce informational uncertainties in the labor market. The following implications, in contrast, are a consequence of referrals improving the quality of the match.

2.3.2 Wage and Turnover Effects

Since the signal about the worker's productivity is less noisy in the referral than in the external market ($\sigma^2_R < \sigma^2_E$), the reservation match quality is higher in the referral than in the external market ($m^*_R > m^*_E$); see Appendix A.3 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, but these effects decline with tenure (see also Appendix A.3).[10]

[10]Note that 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 wage and are less likely to move from job-to-job and from job-to-unemployment at the beginning of the employment relationship.

In our data, we do not directly observe whether a worker obtained the job through a referral. Next, we show that this probability is increasing in the share of existing minority workers in the firm, $S^{\tau-1}_{\text{Min}j}$, a variable that we do observe. Consider a firm with one vacancy in $\tau - 1$ that is filled in period τ with a minority worker. The probability that the minority worker obtained the job through a referral equals:

$$\Pr(\text{Referral—Hire=Minority}) = \frac{S^{\tau-1}_{\text{Min}j} u \Pr(m > m^*_R)}{S^{\tau-1}_{\text{Min}j} u \Pr(m > m^*_R) + S(1-u)\lambda^E_F \Pr(m > m^*_E)}. \quad (2)$$

The denominator is the overall probability that a minority worker was hired, while the numerator is the probability that a minority worker was hired through the referral market. The probability that a minority worker obtained his job through a referral is thus increasing in the share of minority workers in the firm at $\tau - 1$ at a decreasing rate.

In the second part of the empirical analysis, we test whether minority workers initially earn higher wages, but experience lower wage growth, if the share of minority workers of the own type one period before the worker was hired is higher. We also investigate whether the share of workers of the own type initially lowers turnover, but less and less so as workers stay with their firms longer. In Section 4.2, we describe in detail how we account for the systematic sorting of minority groups into firms that typically plagues this type of analysis. We report our baseline results in Section 5.2.1.

3 Data and Background

3.1 Data and Sample Selection

The data used in our analysis come from German Social Security Records covering more than two decades, from 1980 to 2001. They comprise every man and woman covered by the social security system, observed at the 30^{th} of June in each year. Not included are civil servants, the self-employed, and military personnel.[11] The data contain unique

[11]In 2001, 77.2% of all workers in the German economy were covered by social security and are hence recorded in the data (Bundesagentur für Arbeit, 2004).

worker and establishment identifiers[12], as well as an unusually wide array of background characteristics, such as education[13], occupation, and industry. Our definition of ethnic minority groups is based on citizenship.[14] Consequently, individuals with foreign citizenship who were born in Germany are included among the ethnic minority populations.[15] 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).

Our 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 ethnicity composition of each firm's workforce. Second, we are able to follow workers, and their co-workers and firms, over time.

From this data base, we have initially selected all workers aged between 15 and 64 working 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% in one year and 6.9% in 5 years. Hence, we can think of these cities as local labor markets. Second, ethnic minorities are concentrated in large cities. While 23.2% of ethnic minorities live in the four largest cities, only 13.9% of Germans do so. Throughout the paper, we focus on findings for Munich. The Munich metropolitan area consists of 10 districts (*Kreise*), 222 municipalities (*Gemeinden*), and is approximately 70 miles in diameter. Baseline results for the other three metropolitan areas are similar, and can be found in the data appendix (Tables A.1 and A.2).

[12] Throughout the paper, we use the terms workplace, establishments, and firms interchangeably.

[13] To improve the consistency of the education variable in our data, we apply the imputation algorithm suggested by Fitzenberger et al. (2006).

[14] Until 1 January 2000, citizenship in Germany was exclusively based on descent (ius sanguinis) and individuals born in Germany by non-German parents were not automatically granted German citizenship. Naturalization of adults was possible after 15 years of legal residence. Since 1 January 2000, children born by non-German parents who have legally lived in Germany for at least eight years are automatically granted German citizenship.

[15] If an individual changes citizenship over time, we assign her the first citizenship observed in the data.

3.2 Minority Groups in Germany

Next, we provide a brief overview of the main ethnic minority groups in Germany. Large-scale immigration to (West-) Germany started in the mid-1950s as a result of the strong economic growth at that time. Immigrants originated from countries Turkey, Yugoslavia, Italy, Greece, Spain and Portugal. Following the recession in 1973/1974, the active recruitment of immigrants came to a hold. However, subsequent immigration of family members continued. The second big immigration wave to Germany was a result of the collapse of the Former Soviet Union and the political changes in Eastern Europe in the late 1980s and early 1990s. The main immigrant groups of this period were, on the one hand, ethnic German immigrants (so-called *Aussiedler*), mostly from Poland and the Former Soviet Union, and, on the other hand, refugees from the wars in Former Yugoslavia.[16]

Table 1 reports some summary statistics of our sample – workers between 15 and 64 years old covered by the social security system in Munich. In 1990, 13.4% of the workers in our sample are foreign citizens – which we refer to as minority workers. By 2000, this share had increased to 15.6%. In the same year, the share of foreign citizens in the overall population was 8.9% (column (3)), up from 6.7% in 1990 (not reported). The biggest groups come from Germany's traditional guest worker countries Turkey, Yugoslavia, Italy and Greece, who make up more than 50% of Germany's overall minority population in both our sample and in the overall population.

Columns (4) to (6) of Table 1 show the educational attainment of minority workers in our sample. Individuals, in particular those from the guest worker countries Turkey, Yugoslavia, Italy, and Greece, are considerably less educated than Germans: about 13.0% of German workers have no post-secondary education (we label these workers as low-skilled), compared with 41.2% of the minority workers. The share of workers with a college degree (which we label as high-skilled) is 20.2% for German, but only 8.9% for minority workers.

The final column displays, for the year 2000, the average number of years minority workers have lived in Germany. Numbers refer to minorities between 16 and 64 in the

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

overall population, and come from the German Microcensus. Individuals from countries of the first migration wave (e.g. Turkey, Italy and Greece) have stayed in Germany for about 20 years, while individuals from the second migration wave (e.g. Poland and Soviet Union) have resided in Germany for only 10 and 5 years, respectively.

4 Empirical Strategy

We start by describing how we test for the first prediction of our model regarding the persistence in the share of minority workers across firms (Section 4.1). We then turn to the wage and turnover effects of referrals, and explain how we account for the systematic sorting of workers into firms to obtain causal estimates (Section 4.2).

4.1 Referrals and Hiring

We begin with directly estimating equation (1): a firm is more likely to hire a minority worker in period τ the higher the share of minority workers in the firm in the previous period, $\tau - 1$. In our data, there is not only one, but many minority groups (which we index by the subscript g). Assuming that minority workers are connected only with workers from their own group, equation equation (1) becomes:

$$\Pr(\text{Hire=Minority}_g) = \frac{S_{gj}^{\tau-1} u \Pr(m > m_R^*) + S_g(1-u)\lambda_F^E \Pr(m > m_E^*)}{u \Pr(m > m_R^*) + (1-u)\lambda_F^E \Pr(m > m_E^*)}. \qquad (3)$$

This equation now says that the probability that a minority worker from group g is hired is increasing in the existing share of minority workers from that group in the firm. In our baseline specification, we estimate the following regression:

$$H_{gj}^{\tau} = \alpha_0 + \alpha_1 S_{gj}^{\tau-1} + X_j'^{\tau} \alpha_{2g} + Z_{gj}'^{\tau-1} \alpha_3 + \gamma_g^{\tau} + u_{gj}^{\tau}, \qquad (4)$$

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, $X_j'^{\tau}$ is a vector of demand side control variables, $Z'^{\tau-1}_{gj}$ is a vector of supply side control variables, γ^{τ}_{g} denote minority group specific year fixed effects, and u^{τ}_{gj} is an unobserved error term. The key parameter of interest is α_1, which identifies the probability of obtaining a job through a referral: $\alpha_1 = \frac{u \Pr(m > m^*_R)}{u \Pr(m > m^*_R) + (1-u)\lambda^E_F \Pr(m > m^*_E)}$. We show in Appendix A.4 that this 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. For the empirical analysis, we focus on the five main minority groups in the Munich metropolitan area: Yugoslavs, Turks, Austrians, Italians and Greeks.[17]

Firms with a high existing share of workers from a particular group may keep hiring workers from the same group not because of referrals, but because they demand workers with particular skills, and minority workers from that group have different skill levels than German workers or minority workers from other groups. To keep the argument simple, suppose that Turkish workers are predominantly low-skilled, whereas German workers are predominantly high-skilled. Then firms with a large demand for low-skilled workers will hire mostly Turkish workers both in the past and the future, leading to a positive estimate for α_1 even in the absence of referrals. In an attempt to deal with these demand side factors, the control variables in X'^{τ}_{j} include the share of low- and medium-skilled workers and the share of female workers among new hires in period τ, as well as the share of low- and medium-skilled workers and the share of female workers in the firm in period $\tau - 1$. Note that the effect of each of these control variables is allowed to vary by minority group. Similarly, firms may hire workers from a particular minority group simply because they are located in areas where many workers from that group reside. In order to address such supply side factors, the control variables in $Z'^{\tau-1}_{gj}$ additionally include the minority share in the local municipality (there are 222 municipalities in the labor market we consider), the minority share in the industry of the firm (we distinguish between 12 industries), and the predicted minority share based on the occupational composition of the firm (we

[17]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% of all minority observations in the sample. We have also carried out the analysis for the 15 biggest minority groups, which make up 85% of all minority observations, with very similar results.

distinguish between 88 occupations) in $\tau - 1$.[18] Our estimation sample covers the years 1990 to 2001.

4.2 Wage and Turnover Effects of Referrals

Our model predicts that referral hires initially earn higher wages, and are less likely to switch firms, than external hires, and that these effects disappear with tenure. From equation (2), the probability of having obtained the job through the referral market is positively related to the share of workers from the same minority group in the firm one period before the worker was hired. To test the predictions, we estimate the following baseline regression:

$$\ln w_{igjt} = \beta_0 + \beta_1 S_{gj}^{\tau-1} + \beta_2 S_{gj}^{\tau-1} \cdot \text{tenure} + X'_{ijt}\beta_3 + \gamma_t + \delta_i + f_j + \varepsilon_{igjt}, \tag{5}$$

where $\ln w_{ijt}$ is the log daily wage (or an indicator variable equal to 1 if the worker leaves the firm in $t+1$) of worker i belonging to minority group g in firm j in the current time period t. $S_{gj}^{\tau-1}$ is the share of workers of the same minority group in the firm in $\tau - 1$, one period before the worker was hired. Notice the difference between the current time period, denoted by t, and the time period when the worker was hired, denoted by τ. X_{ijt} is a vector of (possibly) worker-, firm-, and time-varying control variables (such as tenure), γ_t, δ_i, and f_j denote year, worker, and firm fixed effects, respectively, and ε_{igjt} is an i.i.d. error term.

The key parameters of interest are β_1 and β_2, where β_1 measures the impact of the share of workers from the same ethnic group at the time of the 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 varies with tenure in the firm. From our model, we expect $\beta_1 > 0$ and $\beta_2 < 0$ in the wage regression, and $\beta_1 < 0$ and $\beta_2 > 0$ in the turnover

[18]For a given minority group g and firm j, the last measure is constructed as $\sum_o S_{go} S_{oj}$ where S_{go} is the share of workers in occupation o in the Munich labor market that belong to minority group g, and S_{oj} is the share of workers in firm j that work in occupation o. This measure thus captures 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.

regression.

Minority workers may systematically sort into firms with a higher share of workers of the same ethnic group, leading to biased estimates of β_1 and β_2. The inclusion of worker fixed effects δ_i eliminates any bias due to the selection of workers of different abilities into firms with a low or high share of workers from the same minority group. Including fixed firm effects f_j accounts for low- or high-wage firms predominantly hiring from a particular minority group. Identification comes from workers moving between firms, and exploits, conditional on worker fixed effects and time-varying supply and demand variables, two sources of variation in $S_{gj}^{\tau-1}$: first, the share of workers from a particular minority group may change over time within the firm, and second, in a given hiring year, the firm may employ different minority groups at varying proportions. As a robustness check, we also report estimates that include firm-year of hire fixed effects (f_j^{τ}), and only use the latter source of variation.

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 (5).[19] This procedure does not yield standard errors. We obtain these via bootstrapping with 30 repetitions.

When estimating (5), we pool all workers, including Germans, in our sample, and interact all variables in (5) with a dummy variable indicating whether the worker is from a minority group. Including Germans in the estimation sample implies that both ethnic minority and German workers are used to estimate the fixed firm effects, leading to more precise estimates.

Our estimation sample covers 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

[19]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.

was hired.[20] We further restrict the sample to low- and medium-skilled workers because of wage censoring. This affects about 50% of the high-skilled, but less than 8% of the medium-skilled and 3% of the low-skilled.[21] Our share variable refers to all workers in the firm, and is computed before these sample restrictions are imposed. To define workers from the same minority group, we use the finest classification in the data (for instance, the workers belonging to the same minority group as a French worker are other French workers, and not other West Europeans).

5 Results

We begin with testing the first implication of our model regarding the persistence in the share of minority workers across firms in Section 5.1. We then turn to the turnover and wage effects of referrals in Section 5.2, where we also discuss the robustness of the results, the heterogeneity of the estimated effects, and productivity spillover effects as an alternative explanation for our findings.

5.1 Referrals and Hiring

We report our baseline results in columns (1) and (2) of Table 2, based on equation (4) described in Section 4.1. In column (1), we control only for minority group specific year fixed effects, a specification that arises directly from the theoretical model and equation (3). The results 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 5.7 percentage points. We report our preferred estimate in column (2), were we add our extensive set of demand and supply side variables. This reduces the estimated effect only slightly, from 5.7 to 5.0 percentage points. As discussed in Section 4.1, this estimate suggests that among minority workers,

[20] 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.

[21] We drop these censored observations from the sample.

around 50% obtain their job through a referral.[22]

In the remaining columns of Table 2, we report results separately by education and age, controlling for the same set of variables as in column (2). We find that the impact of the existing share of workers from a particular minority group in the firm on the share of minority workers from the same group among all new hires declines with the education level of the hire, from 0.644 for the low-skilled to 0.103 for the high-skilled. This is consistent with existing evidence that low-skilled workers are more likely to rely on friends and relatives in their job search process than high-skilled workers (see, for example, Borjas, 1998, Ioannides and Loury, 2004, and Wahba and Zenou, 2005). We find no significant differences by age.

We display the main findings based on the specification that includes the entire set of control variables (compare Table 2, column (2)) for the three other metropolitan areas in Table A.1. In all of these labor markets, the impact of the share of workers from the same minority group in the firm in the previous period on the probability that a minority worker from that group is hired is similar in magnitude.

Our model further predicts that firms with a larger than average share of a particular minority group keep hiring minority workers from that group, and not from other groups. We investigate this by estimating a multinomial logit model on a sample of newly hired minority workers. We include the share of each of the five minority groups in the firm in the previous period as regressors, and additionally control for the education and gender of the new hire, the lagged shares of workers with low and medium education in the firm, the lagged share of women in the firm, and year, district, industry, and occupation fixed effects.[23] Results are presented in Table 3 where we report marginal effects, evaluated at variable means. As predicted by our model, the share of workers from a particular minority group in the firm increases the probability that a worker from the same minority group will be hired (diagonal entries), and typically reduces the probability that a

[22]As a robustness check, we include a full set of firm-minority fixed effects and estimate the model in first differences. Following Arellano and Bond (1991), we instrument the lagged change in the minority group share in a firm with the two period lagged level of the minority share. This reduces the coefficient to 0.316, with a standard error of 0.043.

[23]For computational reasons it is not possible to control for all 222 municipalities in the multinomial logit estimation. Instead we move one level up and include 10 district fixed effects.

worker from other minority groups will be employed (off-diagonal entries). For instance, conditional on the firm hiring a minority worker from one of the five largest groups, an increase in the share of Turkish workers in the firm by 1 percentage point increases the firm's probability of recruiting a Turkish worker by 0.9 percentage points, and reduces the firm's probability of employing an Italian worker by 0.2 percentage points.

5.2 Turnover and Wage Effects of Referrals

Next, we turn to the wage and turnover implications of our model. A higher share of minority workers from the same group in the firm one period before the worker was hired should increase wages, and lower turnover, of minority workers, in particular at the beginning of the employment relationship. These effects should subsequently decline with tenure.

5.2.1 Baseline Results

We report our main results based on equation (5) in Table 4. In Panel A, we report the *overall* impact of the share of workers from the same minority group in the firm one year before the worker was hired ('own share') on wages and turnover decisions of minority workers (that is, without the tenure interaction in equation (5)). We start with OLS estimates and, in addition to the own share, only control for year fixed effects (column (1)). The estimate on the own share variable of -0.190 in the wage regression implies that, for a minority worker, a 10 percentage point increase (which roughly corresponds to an increase of half a standard deviation) in the share of workers from the same minority group in the firm in the year before the hire took place is associated with a wage decrease of 1.90%. Including a full set of control variables[24] reduces this parameter estimate in magnitude to -0.068 (column (2)).[25]

The significant reduction in our parameter estimate due to the inclusion of control

[24]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.

[25]Hellerstein and Neumark (2003) and Åslund and Nordström Skans (2009b) report similar findings for minority groups in the U.S. and Sweden, respectively. Note, however, that these studies refer to the current, as opposed to the initial, share of co-workers from the same minority group.

variables suggests that the sorting of workers into firms is important, and that OLS estimates are therefore biased. Indeed, controlling for worker fixed effects in column (3) leads to a substantial further reduction in the magnitude of the estimated parameter. The impact of the share of workers from the same ethnic group on wages, however, remains negative. It turns positive if we include a full set of fixed firm effects instead of the fixed worker effects (column (4)). As described in Section 4.2, 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 increases the wage of minority workers by 0.42%.

Turning to the turnover regressions, the OLS results in columns (1) and (2) show that a higher share of workers from the same minority group in the firm one year before the hire took place significantly increases the probability that a minority worker leaves the firm. However, once we control for both worker and firm fixed effects, this changes: an increase in the own share by 10 percentage points now reduces the probability of leaving the firm by 0.23 percentage points. This effect is, however, statistically significant only at the 10% level.

According to our model, 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 to switch firms 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 fixed firm and worker effects (column (5)), an increase in the own share by 10 percentage points raises wages by 0.70% and reduces turnover by 0.41 percentage points at the beginning of the employment relationships. Both effects rapidly decrease with tenure.[26]

[26]The wage estimate implies that after 3 1/3 years, the effect should become negative. This is a consequence of the linear specification imposed on the interaction term. Average firm tenure in the data is only 3.1 years, so that the average worker hired through a referral does not experience much of a wage penalty at the end of his employment relationship.

In Panel C of Table 4, we investigate this issue in a slightly different manner. Here, we allow 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). As predicted by our model, 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 by 0.68%, compared to only 0.10% 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 actually increases turnover in subsequent years.

What about the magnitude of these findings? To assess this, one needs to know by how much an increase in the initial share of workers from the same minority group raises the probability of a referral hire. From our model (equation (2)), Pr(Referral—Hire=Minority) = $\frac{S^{\tau-1}_{\text{Min}j}}{S^{\tau-1}_{\text{Min}j}+S\frac{b}{a}}$, where $a = u\Pr(m > m^*_R)$ and $b = (1-u)\lambda^E_F \Pr(m > m^*_E)$. From Table 2 and equation (4), we obtain $\alpha_1 = \frac{a}{a+b} = 0.498$, so that $\frac{b}{a} = \frac{1-\alpha_1}{\alpha_1} = 1.008$. Evaluated at the median minority share in the firm prior to the hire, $\tilde{S}^{\tau-1}_{gj} = 2.9\%$, and the median share of minority workers in the population, $\tilde{S}_g = 1.3\%$, a 10 percentage point increase in the share of minority workers from the same group in the firm in the year before the hire corresponds to an increase in the probability of having obtained the job through a referral by 21.9 percentage points. Consequently, assuming linearity, a referral increases wages in a worker's first year (subsequent years) at the firm by 3.1% (0.5%), and lowers turnover in the first year by 2.9 percentage points. In order to put the wage effect into perspective, Dustmann and Meghir (2005) find that for medium-skilled workers, the return to experience beyond the 4th year in the labor market is 1.2%, while the return to firm tenure is about 2%.

We display findings for the three other metropolitan areas in Table A.2. In all these labor markets, 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 similar in magnitude.

5.2.2 Robustness Checks

We perform a number of robustness checks in Table 5, focusing on the wage regressions that allow the impact of the share of workers from the same minority group at the time of the referral to differ between the first year at a firm and subsequent years. For comparison, column (1) shows our baseline estimate from Table 4, Panel C, 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 estimates increase somewhat in magnitude. In column (3), we only consider the five main minority groups (the same as in Tables 2 and 3), and allow all control variables to have a different effect for each minority group.[27] Again, results are similar to our baseline findings. To control for potential supply side factors, we add in column (4) the share of minority workers from the same group in the industry and municipality one year before the hire as additional controls. Like the corresponding share 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. Our overall conclusions are unchanged.

Our baseline specification includes Germans in the estimation sample (see Section 4.2), and therefore restricts the fixed firm effect to be the same for the minority and German population. In column (5), we estimate equation (5) 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 of minority workers who have just entered the firm. In column (6) we restrict the sample further to minority workers from Germany's guestworker 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

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

(see Table 1). Results are similar to those in column (4).

Finally, in column (7) we include the squared share of workers from the same minority group in the firm at the time of the referral as an additional regressor. This is motivated by equation (2) which says that the probability of having obtained the job through a referral is concave in the own share. In line with this, we find that the impact of the share of workers of the own type is strongly non-linear. This specification implies that, evaluated at the median share of 2.9%, a 10 percentage point increase in the share variable raises wages in the first year by 1.25%, which is almost twice as large as our baseline estimate of 0.68%.

5.2.3 Heterogeneous Effects

Next, we investigate whether the impact of the share of workers from the same minority group in the firm one year before the worker was hired on wages of minority workers varies across subgroups of workers. In Table 6, we distinguish between 'young' (less or equal to 30) and 'old' (older than 30) workers, as well as between low- and medium-skilled workers. Otherwise, the specification is the same as in our baseline (Table 4, Panel C, column (5)). We find that the share of workers from the same minority group in the firm at the time of the referral increases wages of minority workers at the beginning of the employment relationship only among the young and among the low-skilled.

One reason for why the wage effect is particularly pronounced for the low-skilled could be a higher variance of the match-specific productivity, $\sigma^2_{\mu_{\text{low}}} > \sigma^2_{\mu_{\text{medium}}}$, implying that referrals are particularly valuable for the low-skilled.[28] There is some empirical support for this inequality: Adda et al. (2009) find that in Germany, the match quality distribution is more dispersed for the low- than for the medium-skilled.

One explanation for the large wage gains of the young could be that the match quality of young workers is less certain than the match quality of older workers ($\sigma^2_{E_{\text{young}}} > \sigma^2_{E_{\text{old}}}$), but that this uncertainty can be fully reduced when hiring takes place through a referral

[28] To see this, note that the variance of the match quality after signal $\widehat{y}$ is observed is $V(y|\widehat{y}) = \frac{\sigma^2_\mu \sigma^2_i}{\sigma^2_\mu + \sigma^2_i}$, $i = R, E$. Hence, $\frac{d^2 V(y|\widehat{y})}{d\sigma^2_\mu d\sigma^2_i} > 0$. Hence, even if $\sigma^2_{R_{\text{low}}} = \sigma^2_{R_{\text{medium}}}$, $\sigma^2_{\mu_{\text{low}}} > \sigma^2_{\mu_{\text{medium}}}$ implies a greater reduction in noise due to referrals.

($\sigma^2_{R_{\text{young}}} = \sigma^2_{R_{\text{old}}}$). Again, this inequality implies that referrals are particularly valuable for young workers, as they lead to a larger reduction in uncertainty. In line with this reasoning, research by, for instance, Farber and Gibbons (1996) and Altonji and Pierret (2001) highlights that productivity is particularly uncertain for young workers who have just entered the labor market.

5.2.4 Productivity Spillover Effects

The findings are supportive of our referral model in which employees provide their employers with information about potential job market candidates that they otherwise would not have. A possible alternative explanation for the empirical patterns we find is based on productivity spillover effects: minority workers are more productive if they work with workers from their own group than if they work with workers from other minority groups or with natives. The main reason for such productivity spillover effects is a common language shared by individuals from the same country of origin.[29] Spillover effects can potentially explain why firms with a high share of a specific minority group in the past continue to hire from this group. Productivity spillover effects may also be able to account for our findings that minority workers earn higher wages and have lower turnover rates in firms that employed a larger share of workers from their own type in the year before they were hired. Under certain circumstances, they may even provide an explanation for why these wage and turnover effects are particularly strong for workers who have just entered the firm (Table 4, Panels B and C): if the language skills of minority workers, and hence their ability to communicate with natives, improve with tenure in the firm, then (relative) productivity spillover effects from other workers from the same country of origin should decline with time in the firm.

However, if this is the underlying mechanism, then there should be no productivity spillover effects for workers who are identical to native workers in those features that lead to positive spillovers. To check this, we investigate a group of workers that is identical

[29]Productivity spillover effects have been extensively studied among pupils in schools, but little work exists on the level of the firm. The few existing papers focus on a particular industry, or a particular firm within that industry. Examples include supermarket scanning (Mas and Moretti, 2009), fruit picking (Bandiera et al., 2005, 2007), and soccer (Ashworth and Heyndels, 2007).

to natives in their language skills, and very similar in their culture: Austrians. As shown in Table 1, Austrians make up the third largest immigrant group in the Munich labour market. If our findings are driven by productivity spillover effects, the share of Austrians in the firm one year before the worker was hired should have little or no impact on wages and turnover behavior of Austrians. However, as we show in Table 7, we find that a 10 percentage point increase in the share of Austrians in the firm one year before the worker was hired increases wages of Austrians who have just entered the firm by 0.49% – which is similar in magnitude to, and not statistically different from, the corresponding result of 0.69% for non-Austrian minority workers. We also find a significant negative effect of the own share in the firm on the first-year job turnover probability of Austrian workers. The estimated effect is larger in magnitude than for non-Austrian minority workers but again not statistically different. While these findings are difficult to reconcile with a model of productivity spillover effects, they follow from our network model if Austrians and Germans belong to different networks.

6 The Welfare Gain of Referrals

Our baseline findings indicate that a 10 percentage point increase in the share of workers from the own minority group in the firm prior to the hire increases wages in a worker's first year at the firm by 0.68%, and by 0.10% in subsequent years (Table 4, Panel C, column (5)). Moreover, such a 10 percentage point increase implies that the worker is 21.9 percentage points more likely to have obtained his job through a referral. Hence, assuming linearity, a referral raises wages in a worker's first year at the firm by 3.1%, and wages in subsequent years by 0.5%.

What do these numbers imply about how much referrals reduce the uncertainty about the worker's productivity? And by how much do they increase welfare, through noise reduction and better matches? 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 market candidate prior to the hire is the more valuable the slower agents learn.

To illustrate the potential welfare gains due to referrals, we use the structure of our model to uncover these two parameters. 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 ($\Delta \ln w^{Data}_{Entry} = 0.031$) and the difference between the log wage of referral and external hires in subsequent years of the employment relationship ($\Delta \ln w^{Data}_{Subsequent} = 0.005$), to their model equivalents. The model equivalents $\Delta \ln w^{Model}_{Entry}$ and $\Delta \ln w^{Model}_{Subsequent}$ are given by equations (A-11) and (A-13) in Appendix A.5. Both are complicated functions of α and σ^2_R. In our model, the lower σ^2_R (relative to σ^2_E), the larger $\Delta \ln w^{Model}_{Entry}$. Moreover, the higher α, the lower $\Delta \ln w^{Model}_{Subsequent}$.

We compute these model moments for a fine grid of values for α and σ^2_R, for given values of the other parameters in our model. We then pick those values for α and σ^2_R that minimize the sum of the squared distance between the model and the data moments:

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

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 $\sigma^2_R = 0.56$ and $\alpha = 0.48$, implying that referrals reduce the uncertainty about the worker's productivity by 46.8% relative to the external market and that the true productivity of the worker is revealed with a 48% probability in any given period.[30]

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, $\sigma^2_R = \sigma^2_E$. Our findings suggest that welfare increases by 0.75% as a result of the better matches produced through the referral market. While these numbers have to be interpreted with caution, they do suggest

[30] We also simulate the model using alternative values for the bargaining power of workers. For $\gamma = 0.25$, we find optimal values of $\sigma^2_R = 0.32$ and $\alpha = 0.44$; for $\gamma = 0.75$, we find optimal values of $\sigma^2_R = 0.69$ and $\alpha = 0.49$. Among the three sets of results, $\gamma = 0.75$ yields the best fit with our data moments.

that the welfare gains from noise reduction due to referrals may be quite large.

7 Summary and 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 through formal channels or through the network. Using unique matched employer-employee social security data that cover all workers and firms in one large West German metropolitan area over a 20 year period, we find strong support for the predictions of our model. We first show that firms are more likely to hire a minority worker from a particular group, rather than a majority worker or a worker from other groups, if the share of existing minority workers from that group in the firm is higher. We further find that, once we control for the non-random sorting of workers into firms, minority workers earn higher wages, and are less likely to leave their firms, if they were hired by a firm with a larger share of minority workers from their own group and are therefore more likely to have obtained the job through the network. The effects are particularly strong at the beginning of the employment relationship and rapidly decline with tenure in the firm. Our baseline findings indicate that a referral raises wages of workers who have just entered the firm by 3.1%, and wages in subsequent years by on average 0.5%. These wage effects are stronger for young and low-skilled workers who have the most to gain from a referral.

Using the structure of our model, we finally illustrate the welfare gains due to noise reduction through referrals: total welfare in the economy increases by 0.75% as a result of the additional information provided to employers. Overall, these findings support 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 he 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_W^R, 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_W^E, and can choose between W_1^E and U. With probability $(1-\lambda_W^R)(1-\lambda_W^E)$, workers receive neither a referral nor an external offer and remain unemployed. The value of being unemployed therefore equals

$$\begin{aligned} U &= b + \beta\lambda_W^R E\max(W_1^R, U) + \beta(1-\lambda_W^R)\lambda_W^E E\max(W_1^E, U) \quad \text{(A-4)} \\ &\quad +\beta(1-\lambda_W^R)(1-\lambda_W^E)U. \end{aligned}$$

The value of a vacancy can be similarly derived as

$$\begin{aligned} V &= -k + \beta\lambda_F^R E\max(J_1^R, V) + \beta(1-\lambda_F^R)\lambda_F^E E\max(J_1^E, V) \\ &\quad +\beta(1-\lambda_F^R)(1-\lambda_F^E)V, \end{aligned}$$

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

$$k = \beta\lambda_F^R E\max(J_1^R, 0) + \beta(1-\lambda_F^R)\lambda_F^E E\max(J_1^E, 0). \quad \text{(A-5)}$$

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, $\lambda_F^R = u$. The following conditions need to hold for a worker to obtain a referral offer: His 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 $\lambda_W^R = (1-u)v/(1-v)$.[31] 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 $\lambda_W^E = m(u_E, v_E)/u_E$, where $u_E = u(1-\lambda_W^R)$ and $v_E = v(1-\lambda_F^R)$.

A. 2 Steady State Unemployment and Vacancy Rate

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

$$\begin{aligned} \text{outflow unemployment} &= Nu\lambda_W^R(1-G^R(m_R^*)) + Nu(1-\lambda_W^R)\lambda_W^E(1-G^E(m_E^*)) \\ &:= N_0^R + N_0^E, \end{aligned} \tag{A-6}$$

where $G^i(.), i = R, E$, denotes the distribution from which expected match qualities are drawn.[32]

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:

$$\text{inflow unemployment} = N\delta(1-u) + \sum_{i=R,E} \frac{\alpha(1-\delta)\int_{m_i^*}^{\infty}\int_{-\infty}^{y^*} dF^i(y|m^i, \sigma_i^2)dG^i(m^i)/(1-G^i(m_i^*))}{1-(1-\alpha)(1-\delta)} N_0^i. \tag{A-7}$$

A. 3 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 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.

[31] 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%, the probability that a firm with 10 positions has at least 6 vacancies is less than 0.015%.

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

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 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:

$$S_1^i = \frac{m^i + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty} (y - y^*) dF^i(y|m^i, \sigma_i^2) - y^*}{1 - \beta(1-\alpha)(1-\delta)}.$$

Hence,

$$m_i^* = y^* - \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)} \int_{y^*}^{\infty} (y - y^*) dF^i(y|m_i^*, \sigma_i^2). \tag{A-8}$$

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:

$$\begin{aligned}
\overline{w}^i &= \int_{m_i^*}^{\infty} w^i dG^i(m^i) \Big/ (1 - G^i(m_i^*)) \\
&= \gamma \int_{m_i^*}^{\infty} m^i dG^i(m^i) \Big/ (1 - G^i(m_i^*)) + (1-\beta)(1-\gamma)U, i = R, E. \qquad \text{(A-9)}
\end{aligned}$$

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:

$$\overline{w}_2^i = \int_{m_i^*}^{\infty} \frac{\int_{y^*}^{\infty} w_2 dF^i(y|m^i,\sigma_i^2)}{1-F^i(y^*|m^i,\sigma_i^2)} dG^i(m^i) \Big/ (1-G^i(m_i^*))$$

$$= \gamma \int_{m_i^*}^{\infty} \frac{\int_{y^*}^{\infty} y dF^i(y|m^i,\sigma_i^2)}{1-F^i(y^*|m^i,\sigma_i^2)} dG^i(m^i) \Big/ (1-G^i(m_i^*)) \quad \text{(A-10)}$$
$$+(1-\beta)(1-\gamma)U, i = R, E.$$

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 $\Pr(\text{move}|i = E) > \Pr(\text{move—}i = R)$. 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. 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.[33] In this case, the probability that a minority

[33]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 his job through a referral becomes:

$$\Pr(\text{Referral—Hire=Minority}) = \frac{S^{\tau-1}_{\text{Min}j}\tilde{u}\Pr(m > m^*_R)}{S^{\tau-1}_{\text{Min}j}\tilde{u}\Pr(m > m^*_R) + S(1-\tilde{u})\lambda^E_F \Pr(m > m^*_E)},$$

where $\tilde{u}$ is the probability that at least one network member is unemployed.[34] As in the model with one connection, a higher share of minority workers in the firm increases the probability that a minority worker obtained his 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:

$$\Pr(\text{Hire=Minority}) = \frac{S^{\tau-1}_{\text{Min}j}\tilde{u}\Pr(m > m^*_R) + S(1-\tilde{u})\lambda^E_F \Pr(m > m^*_E)}{\tilde{u}\Pr(m > m^*_R) + (1-\tilde{u})\lambda^E_F \Pr(m > m^*_E)}.$$

More than one ethnic 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:

$$\Pr(\text{Referral}|\text{Hire=Minority}_g) = \frac{(S^{\tau-1}_{gj}(\gamma_{gg}-\gamma_{Gg}) + \sum_{g'\neq g} S^{\tau-1}_{g'j}(\gamma_{g'g}-\gamma_{Gg}) + \gamma_{Gg})u\Pr(m > m^*_R)}{\begin{array}{r}[(S^{\tau-1}_{gj}(\gamma_{gg}-\gamma_{Gg}) + \sum_{g'\neq g} S^{\tau-1}_{g'j}(\gamma_{g'g}-\gamma_{Gg}) + \gamma_{Gg})u\Pr(m > m^*_R) \\ + S_g(1-u)\lambda^E_F \Pr(m > m^*_E)]\end{array}}.$$

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 his 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:

$$\Pr(\text{Hire=Minority}_g) = \frac{\begin{array}{r}[(S^{\tau-1}_{gj}(\gamma_{gg}-\gamma_{Gg}) + \sum_{g'\neq g} S^{\tau-1}_{g'j}(\gamma_{g'g}-\gamma_{Gg}) + \gamma_{Gg})u\Pr(m > m^*_R) \\ + S_g(1-u)\lambda^E_F \Pr(m > m^*_E)]\end{array}}{u\Pr(m > m^*_R) + (1-u)\lambda^E_F \Pr(m > m^*_E)}.$$

[34]For simplicity, we have assumed that in case a worker knows more than one unemployed worker, he randomly refers one of them to his employer. If instead he 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-9). 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, $\overline{w}^i_2$, given by equation (A-10). Let $\overline{w}^i_{sub}$, $i = R, E$, denote this mean wage for workers who have been hired through the external or referral market, respectively. $\overline{w}^i_{sub}$ is given by

$$\overline{w}^i_{sub} = \frac{(1-\alpha)\overline{w}^i + \frac{\alpha}{\delta} \int\limits_{m_i^*}^{\infty} (\int\limits_{y^*}^{\infty} dF^i) dG^i / \int\limits_{m_i^*}^{\infty} dG^i \overline{w}^i_2}{(1-\alpha) + \frac{\alpha}{\delta} \int\limits_{m_i^*}^{\infty} (\int\limits_{y^*}^{\infty} dF^i) dG^i / \int\limits_{m_i^*}^{\infty} dG^i}, i = R, E. \tag{A-12}$$

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

$$\Delta \ln w^{Model}_{Subsequent} = \ln \overline{w}^R_{sub} - \ln \overline{w}^E_{sub}. \tag{A-13}$$

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

Table A.3 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%). 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.3 and a fine grid of values for α and σ^2_R. 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-8).

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

$$\begin{aligned} y^* &= (1-\beta)U \\ &= b + \beta\gamma(1-u)v/(1-v)\int_{m^*_R}^{\infty}\Big(\frac{m^R - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)}\int_{y^*}^{\infty}(y-y^*)dF^R(y|m^R,\sigma^2_R)}{1-\beta(1-\alpha)(1-\delta)}\Big)dG^R(m^R) + \\ & \quad \beta\gamma(1-(1-u)v/(1-v))\lambda^E_W\int_{m^*_E}^{\infty}\Big(\frac{m^E - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)}\int_{y^*}^{\infty}(y-y^*)dF^E(y|m^E,\sigma^2_E)}{1-\beta(1-\alpha)(1-\delta)}\Big)dG^E(m^E). \end{aligned}$$

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

$$\begin{aligned} k = & \ \beta(1-\gamma)u\int_{m^*_R}^{\infty}\Big(\frac{m^R - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)}\int_{y^*}^{\infty}(y-y^*)dF^R(y|m^R,\sigma^2_R)}{1-\beta(1-\alpha)(1-\delta)}\Big)dG^R(m^R) + \\ & \beta(1-\gamma)(u/v)\Big(1-\frac{(1-u)v}{(1-v)}\Big)\lambda^E_W\int_{m^*_E}^{\infty}\Big(\frac{m^E - y^* + \frac{\beta\alpha(1-\delta)}{1-\beta(1-\delta)}\int_{y^*}^{\infty}(y-y^*)dF^E(y|m^E,\sigma^2_E)}{1-\beta(1-\alpha)(1-\delta)}\Big)dG^E(m^E). \end{aligned}$$

5) The equality of the outflow out of unemployment, given by equation (A-6), and the inflow into unemployment, given by equation (A-7):

$$\begin{aligned} u\frac{(1-u)v}{(1-v)}(1-G^R(m^*_R)) \ &+ \ u\Big(1-\frac{(1-u)v}{(1-v)}\Big)\lambda^E_W(1-G^E(m^*_E)) \\ &= \ \delta(1-u) + \frac{\alpha(1-\delta)\int_{m^*_R}^{\infty}F^R(y^*|m^R,\sigma^2_R)dG^R(m^R)}{1-(1-\alpha)(1-\delta)}u\frac{(1-u)v}{(1-v)}. \\ &+ \ \frac{\alpha(1-\delta)\int_{m^*_E}^{\infty}F^E(y^*|m^E,\sigma^2_E)dG^E(m^E)}{1-(1-\alpha)(1-\delta)}u\Big(1-\frac{(1-u)v}{(1-v)}\Big)\lambda^E_W. \end{aligned}$$

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^2_R the two model moments given by equations (A-11) and (A-13), using again the parameter values in Table A.3. We finally compute the squared distance between the model and data moments, and select those values of α and σ^2_R that minimize this distance.

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Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Share of Workforce Munich (in %)		Share of Population Germany (in %)	Share of Educational Attainment in 2000, Munich (in %)			Years since in Germany
	1990	2000	2000	Low	Medium	High	2000
Germans	86.6	84.4	91.1	13.0	66.9	20.2	
Ethnic Minorities	13.4	15.6	8.9	41.2	49.9	8.9	17.7
Ethnic Minorities only							
Former Yugoslavia	27.6	25.3	15.2	42.5	55.7	1.8	19.0
Turkey	20.3	17.2	27.4	56.4	41.6	2.0	19.8
Austria	15.9	11.1	2.6	14.0	70.4	15.7	23.5
Italy	8.0	7.6	8.5	42.8	50.9	6.3	22.9
Greece	6.6	5.8	5.0	60.7	35.0	4.3	22.2
Poland	1.5	2.1	4.1	35.6	54.2	10.2	10.2
Former Soviet Union	0.1	1.2	3.8	36.5	40.4	23.1	5.1
Other Western Europe	6.9	8.1	10.3	27.4	43.4	29.2	20.1
Central and Eastern Europe	4.4	6.4	3.4	30.4	58.0	11.7	12.0
Asia	3.5	6.8	11.5	53.9	34.9	11.2	10.5
North America	2.0	1.6	1.7	22.7	41.7	35.6	16.4
Africa	1.3	3.4	4.1	58.4	35.1	6.6	11.6
Central and South America	0.6	1.1	1.2	40.1	41.5	18.4	10.6
Others	1.5	2.2	1.2	29.7	59.3	11.0	12.9

Note : The first two columns show the share of ethnic minorities in our sample (Munich) in 1990 and 2000. For comparison, the third column displays the share of ethnic minorities in the overall population, obtained from the German Statistical Office. Columns (3) to (4) report the share of low-, medium-, and high-skilled workers in our sample. Low-skilled workers are workers who enter the labor market without post-secondary education. Medium-skilled workers are workers who completed an apprenticeship. High-skilled workers are workers with a college or university degree. The last column reports the average number of years ethnic minorities between 16 and 64 (including those born in Germany) have spent in Germany, obtained from the German Microcensus.
Sources : Columns (1), (2), and (4) to (6): Social Security Data, Munich, 1990 and 2000. Column (3): Statistical Office. Column (7): German Microcensus.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All		Low-skilled	Medium-skilled	High-skilled	Age ≤30	Age >30
own share, τ-1	0.568	0.498	0.644	0.419	0.103	0.516	0.490
	(0.016)**	(0.015)**	(0.024)**	(0.017)**	(0.018)**	(0.018)**	(0.019)**
Firms	95,158	95,158	59,449	85,850	28,785	78,136	80,337
Observations	2,116,675	2,116,675	967,415	1,695,295	421,040	1,549,110	1,411,500
Year x Minority FE	yes	yes	yes	yes	yes	yes	yes
Additional Control Variables	no	yes	yes	yes	yes	yes	yes

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 controls 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). Regressions in columns (3) to (7) use the minority-specific shares among new hires of the specified education level or age as the dependent variable, and include the same set of covariates as in column (2).
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 : Social Security Data, Munich, 1990-2001.

Table 3: The Share of Workers from the Same Ethnic Group and the Probability of Getting Hired, Multinomial Logit Model

	Greece	Italy	Yugoslavia	Austria	Turkey
Minority Share Greece, τ-1	**0.639**	-0.014	-0.418	-0.348	0.142
	(0.029)**	(0.031)	(0.074)**	(0.043)**	(0.069)*
Minority Share Italy, τ-1	0.001	**0.679**	-0.221	-0.215	-0.245
	(0.018)	(0.018)**	(0.039)**	(0.021)**	(0.042)**
Minority Share Yugoslavia, τ-1	-0.061	-0.179	**0.770**	-0.209	-0.322
	(0.011)**	(0.013)**	(0.021)**	(0.011)**	(0.026)**
Minority Share Austria, τ-1	-0.079	-0.008	-0.003	**0.355**	-0.264
	(0.025)**	(0.023)	(0.042)	(0.021)**	(0.041)**
Minority Share Turkey, τ-1	0.027	-0.199	-0.441	-0.308	**0.922**
	(0.019)	(0.023)**	(0.059)**	(0.023)**	(0.066)**
Observations			292,837		

Note: Estimates reported are marginal effects from a multinomial logit model, evaluated at variable means. Control variables included, besides the shares of the five main minority groups in the previous period, are the education level and gender of the new hire, year fixed effects, the lagged shares of workers with low and medium education in the firm, the lagged share of women in the firm, 10 district fixed effects, 12 industry fixed effects and 88 occupation fixed effects. Standard errors are clustered at the firm level.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Social Security Data, Munich, 1990-2001.

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	-0.190	-0.068	-0.030	0.049	0.042
	(0.005)**	(0.004)**	(0.006)**	(0.010)**	(0.006)**
Turnover					
own share, τ-1	0.122	0.010	0.039	-0.060	-0.023
	(0.003)**	(0.003)**	(0.009)**	(0.006)**	(0.014)
Panel B: Tenure Interactions					
Wages					
own share, τ-1	-0.187	-0.065	-0.012	0.106	0.070
	(0.005)**	(0.004)**	(0.006)**	(0.010)**	(0.005)**
own share, τ-1 X tenure	0.001	-0.001	-0.015	-0.020	-0.021
	(0.001)	(0.001)	(0.001)**	(0.002)**	(0.001)**
Turnover					
own share, τ-1	0.142	0.043	0.023	-0.060	-0.041
	(0.004)**	(0.004)**	(0.009)**	(0.009)**	(0.012)**
own share, τ-1 X tenure	-0.010	-0.012	0.020	-0.001	0.019
	(0.001)**	(0.001)**	(0.002)**	(0.002)	(0.001)**
Panel C: First Year versus Subsequent Years					
Wages					
own share, τ-1, first year	-0.195	-0.073	-0.018	0.101	0.068
	(0.004)**	(0.003)**	(0.007)**	(0.009)**	(0.006)**
own share, τ-1, subsequent years	-0.163	-0.064	-0.046	0.019	0.010
	(0.006)**	(0.004)**	(0.007)**	(0.011)	(0.005)*
Turnover					
own share, τ-1, first year	0.149	0.057	0.017	-0.062	-0.064
	(0.005)**	(0.005)**	(0.009)*	(0.010)**	(0.013)**
own share, τ-1, subsequent years	0.078	-0.020	0.068	-0.059	0.029
	(0.004)**	(0.003)**	(0.010)**	(0.007)**	(0.013)*

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 (4), and bootstrapped in column (5). The number of observations is 5,834,568 (of which 1,083,117 refer to minority workers) in the wage regressions and 5,323,163 (986,563) in the turnover regressions.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Social Security Data, Munich, 1990-2001.

Table 5: The Impact of the Share of Workers from the Same Minority Group on Wages: 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) Squared Specification
own share, τ-1, first year	0.068	0.096	0.073	0.059	0.049	0.054	0.144
	(0.006)**	(0.010)**	(0.008)**	(0.007)**	(0.008)**	(0.008)**	(0.011)**
own share squared, τ-1, first year							-0.119
							(0.017)**
own share, τ-1, subsequent years	0.010	0.021	0.012	0.002	-0.017	-0.017	0.044
	(0.005)*	(0.009)**	(0.007)	(0.006)	(0.007)*	(0.009)	(0.010)**
own share squared, τ-1, subsequent years							-0.060
							(0.013)**
Observations	5,834,568	5,834,568	5,523,809	5,834,568	1,083,117	678,431	5,834,568

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 between a worker's first year at the firm and a worker's subsequent years at the firm. For comparison, we first display our baseline results from Table 4, Panel C, column (5), in column (1). Column (2) allows for a fixed firm-year effect. Column (3) considers only the 5 main minority groups, and allows all control variables to vary for each of the 5 minority group. In column (4), we add the share of minority workers from the same group in the industry and municipality one year before the hire as additional controls. Like the corresponding share at the firm level, their effect is allowed to vary between a worker's first year and subsequent years at the firm. In column (5), we 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). Results in column (7) correspond to the baseline specification, but we add squared terms of the share variables. All regressions include worker and firm fixed effects.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Social Security Data, Munich, 1990-2001.

Table 6: The Impact of the Share of Workers from the Same Minority Group on Wages: Heterogeneity

	Age		Education	
	Age ≤30	Age >30	Low-skilled	Medium-skilled
own share, τ-1, first year	0.134	0.002	0.101	0.009
	(0.010)**	(0.007)	(0.008)**	(0.008)
own share, τ-1, subsequent years	0.055	-0.034	0.035	-0.040
	(0.014)**	(0.007)**	(0.009)**	(0.008)**

Note: The table investigates whether the benefits of referrals are heterogeneous. We report results separately by age and by education. Specifications correspond to our baseline specification in Table 4, Panel C, column 5, and control for both firm and worker fixed effects.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Social Security Data, Munich, 1990-2001.

Table 7: Alternative Explanation: Productivity Spillover Effects

	Wages		Turnover	
	Austrians	Non-Austrians	Austrians	Non-Austrians
own share, τ-1, first year	0.049	0.069	-0.178	-0.057
	(0.025)*	(0.005)**	(0.074)*	(0.016)**
own share, τ-1, subsequent years	-0.025	0.013	0.049	0.025
	(0.023)	(0.006)*	(0.070)	(0.015)

Note: To test for productivity spillover effects, we display results separately for Austrians (who speak the same language as and are culturally very similar to Germans) and other non-minorities. Specifications correspond to our baseline specification in Table 4, Panel C, column 5, and control for both firm and worker fixed effects.
Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.
Source: Social Security Data, Munich, 1990-2001.

Table A.1: The Share of Workers from the Same Ethnic Group and the Probability of Getting Hired, Other Cities

	Munich	Frankfurt	Cologne	Hamburg
own share, τ-1	0.498	0.558	0.544	0.530
	(0.015)**	(0.007)**	(0.014)**	(0.008)**
Firms	95,158	87,527	107,354	97,047
Observations	2,116,675	1,927,640	2,388,585	2,212,040

Note: The table reports the results from regressing the minority-specific shares of new hires for the 5 largest minority groups in each metropolitan area on the corresponding shares of minority workers in the firm in the previous year. Included controls are 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 controls are interacted with minority group dummies. In addition, the regression includes minority/year fixed effects, the minority share in the local community, the minority share in the industry of the firm, and the predicted minority share based on the occupational composition of the firm (compare Table 2, column (2)). 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 : Social Security Data, Munich, Frankfurt, Cologne, and Hamburg, 1990-2001.

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, first year	0.068	0.074	0.128	0.062
	(0.006)**	(0.007)**	(0.010)**	(0.011)**
own share, τ-1, subsequent years	0.010	-0.001	0.056	0.003
	(0.005)*	(0.008)	(0.012)**	(0.011)
Turnover				
own share, τ-1, first year	-0.064	-0.129	-0.055	-0.127
	(0.013)**	(0.018)**	(0.021)**	(0.017)**
own share, τ-1, subsequent years	0.029	0.023	0.054	0.063
	(0.013)*	(0.019)	(0.017)**	(0.019)**

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 between a worker's first year at the firm and a worker's subsequent years at the firm. 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 C, column (5).

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

Source : Social Security Data, Munich, Frankfurt, Cologne and Hamburg, 1990-2001.

Table A.3: 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.