How Much Do Employers Learn from Referrals?*

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Abstract: This paper tests the hypothesis that referrals from various sources provide employers with more information about job applicants than they would have without a referral. I use data that contain information on two workers in the same job, allowing me to cancel out differences in job and firm characteristics and control for the possibility that workers with referrals from different sources (or no referral at all) might sort into jobs that put different weights on individual performance. The estimation results are consistent with referrals from current employees, as well as from other firms or labor unions, providing employers with more information than they would have otherwise. Additionally, it appears as though hiring through friends or relatives of the employer may involve some favoritism that results in employers collecting less information than they would otherwise. I find no evidence that referrals from community organizations or other sources have any effect.

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This paper tests the hypothesis that referrals from various sources provide employers with more information about job applicants than they would have without a referral. The focus is on two testable implications of this hypothesis. First, since more precise information at the time of hiring will make employers more confident in their initial estimates of a worker's productivity, the initial wages of workers who received an informative referral should be more correlated with the employers' evaluations of their productivity than will the wages of workers who are hired without a referral. Secondly, employer learning will have less of an effect on the wages of workers who received informative referrals than it will on the wages of workers who received no referral at all because employers will have less to learn about referred workers' productivity.

The importance of referrals to both the recruitment efforts of firms and the job search of individuals is well known. Rees and Schultz (1970) found that referrals are the most commonly used informal recruitment channel, and are the preferred method of recruitment for some firms. Holzer (1987) found that referrals from employees and other employers produce new hires with higher performance and lower turnover. Holzer (1988), and Blau and Robins (1990) present evidence suggesting that referrals from friends and family members are more effective at producing job offers and acceptances than are other search methods.

The idea that referrals provide employers with more precise information than other hiring channels do is not new. Rees and Schultz (1970) argue that referrals being informative explains their findings. It also provides an intuitively appealing explanation for the other observations noted above. All of these observations, however, have alternative explanations, leaving open the question of whether or not referrals really are as informative as we think they are.

Perhaps the simplest of the other explanations for the previous literature's observations about referrals is that referred workers are drawn from a pool with a higher average productivity. As Kugler (2003) and others have suggested, referred workers might also be preferred by some employers because the employee who referred them can exert some peer pressure. Reynolds (1951) argues that the use of referrals produces "congeniality in the work force" and new hires who live close to the plant, both of which improve retention. Fernandez and Weinberg (1997) suggest that the effectiveness of referrals at producing job offers may stem from referred workers having inside information about that firm's hiring practices. Finally, Loury (2006) provides evidence that, in some cases, the lower turnover of referred workers might be due to referrals being used as a last resort by workers who have few alternatives.

The only previous work to test the hypothesis that referrals provide employers with more precise information than other recruiting methods is Simon and Warner (1992). Using the matching framework developed by Jovanovic (1979), they argue that if referrals reduce uncertainty about match productivity they will result in higher initial wages and lower average wage growth on the job, as well as lower quit rates. Their estimates from a sample of scientists and engineers support these predictions.

There are a few reasons to question whether the empirical results of Simon and Warner (1992) are due to the informational content of referrals or driven by other factors. First, as they acknowledge, they cannot distinguish the predictions of their model from one in which referred workers simply benefit from favoritism. Their predictions would also follow if referred workers were initially more productive than others and non-referred workers underwent additional training on the job to catch up.[1] Finally, their estimates do not allow for the possibility that referrals sort workers into different types of jobs than other recruiting channels do, as is predicted by Kugler (2003) and suggested by the empirical results of Devaro (2005).[2]

The tests in the current paper are based on previous work on statistical discrimination and the tested predictions hold in any environment in which wages are based on expected productivity, including the matching framework used by Simon and Warner (1992). Aigner and Cain (1977) point out that if employers obtain a more reliable signal of productivity for one group than for another the wages of workers from the group that is less well evaluated will vary less with the productivity of those workers than will the wages of the other group. Pinkston (2003) performs tests for both this prediction and the prediction that employer learning has a greater impact on the wages of women than on the wages of men. The current paper performs the same tests, but considers the information employers obtain from different types of referrals

[1] See Mortensen (1988) for a discussion of how similar the empirical implications of matching and on-the-job training can be.

[2] Their relatively homogenous sample may alleviate, but does not eliminate this problem. It is unlikely that all jobs that hire engineers or scientists put the same amount of weight on individual performance when setting wages and are uniform in other unobserved qualities.

compared to hiring without a referral.

The estimation in this paper uses data from the 1982 Employment Opportunity Pilot Project (EOPP) survey of employers. An important advantage of this data is that a subset of the establishments report information on two workers in the same job. I exploit this subset to cancel out differences in job and firm characteristics and control for the possibility that workers with referrals from different sources (or no referral at all) might sort into jobs that put different weights on individual performance.

The estimation results provide evidence consistent with referrals from current employees, as well as other firms or labor unions, providing employers with more information than they would have otherwise. Additionally, it appears as though hiring through friends or relatives of the employer may involve some favoritism that results in employers collecting less information than they would otherwise. I find no evidence that referrals from schools, community organizations or other sources provide any useful information. The importance of looking at the difference between two workers in the same job is confirmed by evidence that referrals from the employer's friends and relatives are associated with jobs that put more weight on performance than jobs that are not associated with a referral.

In what follows, I first present a brief discussion of how differences in the reliability of initial productivity signals affect wages. Section 2 describes the data and estimation used in this paper. Section 3 presents estimation results, and Section 4 concludes.

1 Wages with Noisy Productivity Signals

The empirical tests conducted in this paper are based on the framework developed in Pinkston (2003) to test the hypothesis that employers are better able to evaluate the ability of men at the time of hiring than the ability of women. Whether one is considering differences based on gender or the source of a referral the idea is the same: The more accurate the employer's initial signal of worker productivity is, the more that worker's wage will be correlated with the employer's assessment of the worker's ability and the less employer learning will affect wages as tenure increases.

Suppose a firm observes a signal of productivity for each worker i who received a referral of type j at the time of hiring:

$$s_{ij} = \mu_{0i} + \varepsilon_{ij},$$

where μ_{0i} is work i's productivity, $\varepsilon_{ij} \sim N\left(0, \sigma_{\varepsilon j}^2\right)$ and $\sigma_{\varepsilon j}^2$ varies by referral type j. This signal contains any information gathered from initial interviews and tests, as well as whatever the referrer said about the worker. The important assumption at this point is that any information contained in a referral affects the variance of the initial signal around the worker's true productivity.

Also assume the employer observes a vector of worker characteristics X_i and starting productivity is a known linear function of X_i and an error term:

$$\mu_{0i} = X_i\beta + v_i,\ v_i \sim N\left(0, \sigma_v^2\right), \tag{1}$$

where β is common knowledge and σ_ν^2 is the same for all groups. Letting $\widetilde{s}_{ij}$

denote the part of s_{ij} that is not correlated with X_i, the conditional expectation of productivity given X_i and s_{ij} is

$$E\left(\mu_{0i}|X_i, s_{ij}\right) = X_i\beta + \alpha_j \widetilde{s}_{ij} \tag{2}$$

where $\alpha_j = \frac{\sigma_v^2}{\sigma_{\varepsilon j}^2+\sigma_v^2}$. It is now easy to see that the more precise the signal is from a referral of type j, the smaller $\sigma_{\varepsilon j}^2$ is and the larger α_j is.

The assumption implicit in equation (1) that initial productivity does not vary by group is made for the sake of simplicity. The implications developed in Pinkston (2003) and applied here are robust to groups differing in productivity, as long as the variance of productivity that is not explained by observable characteristics, σ_v^2, is the same for all groups.[3] As a result, the empirical results of this paper can not be explained by referred workers being more capable, or performing better due to peer pressure. Similarly any wage premium due to favoritism should be captured by group dummy variables without affecting α_j, unless that favoritism causes employers to bypass their normal screening practices.

Of course, we do not observe the initial signal s_{ij} in the data.[4] What we do observe is an employer-provided evaluation of the worker's productivity at some tenure t, as well as a retrospective evaluation of initial productivity taken at t. Assume for now that the evaluation of productivity at t is

$$P_{tj} = S_{tj} + Z_t\gamma,$$

[3] This is a generalized version of the result in Aigner and Cain (1977) where the weight the conditional expectation of a worker's productivity places on a signal does not vary with average group productivity.

[4] Note that, even though we observe the type of referral that worker's receive, we cannot observe the information the referrer passed on to the employer.

where S_{tj} is an estimate of initial ability based on the initial signal s_{ij} and performance on the job, and $Z_t\gamma$ is the known effect of tenure and training on productivity. As Pinkston (2003) discusses in greater detail, the variance of S_{tj} is higher for higher values of the initial signal's variance, $\sigma^2_{\varepsilon j}$; however, it also decreases in tenure faster for higher values of $\sigma^2_{\varepsilon j}$.[5] In other words, the precision of the productivity measure is increasing in tenure for all workers, but increases more quickly for groups with less precise initial signals.

If we assume that the retrospective measure of initial productivity in the data is S_{tj}, we can write the estimated wage equation as

$$w_{0j} = X\beta + \alpha_j S_{tj} + \phi, \tag{3}$$

where $\phi = \alpha_j\left(\widetilde{s}_j - S_{tj}\right)$. The estimated coefficient $\widehat{\alpha}_j$ is biased downward since ϕ is unobserved and correlated with S_{tj}; however, it is less biased for larger values of $\sigma^2_{\varepsilon j}$, implying that the estimated coefficients understate differences between groups. A larger concern is that this bias might vary with tenure since S_{tj} will be less precise on average for a group that has lower average tenure.[6]

Finally, assuming that the measure of productivity at tenure t, P_{tj}, is an unbiased measure of actual productivity at t, μ_t, the current wage can be written as

$$w_{tj} = E\left(\mu_t | X, P_t\right) = X\beta_{tj} + \alpha_{Pj} P_{tj}. \tag{4}$$

The coefficient α_{Pj} increases in tenure as employers learn and P_{tj} becomes more

[5] S_{tj} can be modeled using a standard Bayesian updating argument, making it a weighted average of the employer's initial signal and a sequence of per period performance observations.

[6] This is assuming the worst case scenario in which the retrospective evaluation in the data is S_{tj}, not s_j (or s_j plus an error term). If the employer reports what he thought of the worker at the time of hiring or the worker's observed performance in $t = 1$, and not what he now thinks of the worker's initial ability as assumed here, this is not a problem.

precise; however, it increases more slowly the more precise initial information is. In other words, the more information the employer had initially, the less important later learning is. Furthermore, at $t = 0$, α_{Pj} is an unbiased estimate of α_j from equation (3), which is especially important given the potential bias in equation (3).[7]

2 Data and Estimation

2.1 The EOPP Data

This paper uses data from the 1982 survey of the Employment Opportunity Pilot Project (EOPP), which contains responses from 3,420 establishments in 28 survey sites. The 1982 survey followed the original 1980 EOPP survey, which was designed to evaluate the effects of a job search and training program.[8] The 1980 survey oversampled establishments with a high proportion of low-wage employees, and the 1982 survey attempted to follow up with the same establishments. In both surveys each establishment was asked for information on the last worker hired, including evaluations of the worker's current productivity and productivity in the first two weeks on the job, as well as starting wage and current wage. Only the 1982 survey contains the information on recruiting

[7] This is assuming that employers learn about workers with different types of referrals at the same rate. If they learn more slowly about one group, estimates based on equation (3) might suggest that group's initial signals are less reliable than they really are; however, the slower rate of learning would counteract the greater importance of employer learning caused by less reliable initial signals. Therefore, if both starting wage estimates and results based on employer learning suggest that employers receive less reliable signals for one group than for another, we can be confident that our results are not due to this bias.

[8] The 28 survey sites include 9 "pilot sites" that had the program and 19 control sites. Some of the sites where SMSAs, while others where rural areas.

methods this paper requires.

An important feature of the 1982 EOPP data is that they contain a subsample of roughly 600 establishments that report data on a second worker hired for the same job as the last worker hired.[9] Differencing two workers in the same job and establishment reduces any bias caused by workers with different types of referrals (or no referral) being in different types of jobs. (The next subsection discusses this in greater detail.) For the sake of comparison, I restrict all estimates to this subsample even when those estimates do not use the difference between the two workers.[10]

The productivity evaluations in the data are the employer's ranking of the worker's productivity in that job on a scale of zero to 100. A rating of 100 indicates the highest possible productivity of a worker in that position. This is explained to the respondent, and they are then asked to rate each worker (and the "typical worker") at three different points: the first two weeks on the job, from the third to the twelfth week, and at either the date of the interview or the last week the worker was employed by the firm.[11] I use the first and last of these evaluations and refer to them as "initial productivity" and "current

[9] The survey explicitly states that this second employee should be someone who was "hired for the same or similar position" as the last worker hired, and job characteristics like occupation are recorded once for the worker pair. The distribution of starting wage differences is consistent with these workers at least being in similar jobs: the median of the absolute value of starting wage differences is only \$0.10, and 90 percent differ by \$1.10 or less. One pair of workers are an obvious outlier with a starting wage difference of \$9.50 per hour. Since they also differ in age by 32 years, this pair was likely not hired for the same job and is excluded.

[10] The primary difference between the subsample that has data on two workers and the rest of the sample is that establishments that report data on two recently hired workers tend to hire more frequently, as one might expect. When a dummy variable for the worker being the second worker is included in wage regressions, the coefficient is always small and insignificant.

[11] If the employee in question is still with the establishment, which describes 67% of observations, the wage and performance evaluation provided are taken at the time of interview. If the employee no longer works at the firm, the wage and performance evaluation used are the most recent available.

productivity", respectively.

The data also contain questions about how the worker was hired; i.e., using a newspaper add, a referral from a current employee, etc. This allows me to separate workers who were hired using a referral from workers who were not, and identifies the source of the referral. Since the source of a referral likely affects how informative it is, I divide my sample into workers who were referred by an employee of the firm, workers referred by a friend or relative of the employer, workers referred by another employer or a labor union, all other referrals and no referral at all.[12]

Limiting attention to establishments that report at least some information on two workers leaves 659 establishments (and worker pairs). I then drop 50 worker pairs in which the workers' pay is based on commission, tips or a piece-rate scale; 12 pairs in which one worker's start date was more than 4 years before the interview date; and 2 pairs in which one worker was younger than 16.[13] Since all observations are from the same survey year, I do not adjust for inflation. The resulting sample has roughly 500 worker pairs and 1000 individual workers. All tables that present estimates also present the number of observations used.

[12] Preliminary estimation that separated workers who were friends of employees from workers who were family of employees found similar results for both groups. I group these workers together in what follows for the sake of simplicity.

I group referrals from friends and family of the employer together, and group referrals from other employers with those from labor unions due to the small sample size. Preliminary estimation supports both of these groupings. "Other" referrals come from schools, employment agencies, community organizations, etc.

[13] Workers paid by piece-rate, commission or tips are excluded because such pay reflects the worker's actual performance and not the employer's perception of ability, which could bias effects of performance upwards. Workers who started more than four years before the interview date are excluded because their employers are outliers in terms of how infrequently they hire. Previous versions of this paper, however, obtained qualitatively similar results without either of these restrictions.

Table 1 presents summary statistics for the sample. The average starting wage is \$4.71 and the average current wage is \$5.46. The average worker has 10.7 months tenure with the employer, and almost 44 months of prior experience that the employer believes "had some application to the position". The average initial productivity of a worker, on a scale of 0 to 100, is 53.08, and the average current productivity is 77.26. About 44% of the sample of 1052 workers had no referral, 26% were referred by an employee of the firm, 6% by a friend or family member of the employer, 6% by another employer or a labor union, and 18% were referred by some other source.

Table 2 presents summary statistics separately for each referral type. Although the number of observations varies depending on the regression, there are up to 269 workers who were referred by an employee of the company, 65 referred by a friend or family member of the employer, 59 referred by another employer or a labor union, and 189 referred by some other source.

There are obvious differences in worker and job characteristics for the different referral types. The wages and initial productivity of workers with referrals from other firms or unions are significantly higher than the wages of workers with no referral, while the wages and initial productivity of workers with a referral from community groups, schools, etc. are significantly lower. The average worker who was referred by an employee or by a friend or relative of the employer works in an establishment of fewer than 60 workers, while the average worker who was hired without a referral is in an establishment with 185 workers.[14]

[14] Differences in tenure are likely related to differences in establishment size. Because the survey is based on the last worker hired, tenure is at least as much of an establishment characteristic as an individual match characteristic.

Workers who were referred by employees are more likely to be in professional, managerial and technical occupations than are workers with no referral, and are less likely to be in bench work occupations.

2.2 Estimation

In all of the estimation that follows, data from the different referral groups are pooled together. Regressions based on equation (3) take the form

$$w_{0j} = X\beta + \alpha S_{tj} + \sum_j \left(\gamma_j D_j + \alpha_j \cdot D_j \cdot S_{tj}\right) + \phi, \qquad (5)$$

where D_j are dummy variables for referral group, the omitted group is those with no referral, and X contains a constant. α measures the effect of the productivity evaluation for those hired without referrals, and α_j captures the difference in the effect of productivity for group j relative to the group without referrals.

The current wage regressions follow an analogous form, except that α_{Pj} is approximated by a linear interaction with tenure:

$$w_{tj} = X\beta_{tj} + \alpha_0 P_{tj} + \alpha_t t P_{tj} + \sum_j \left(\gamma_j D_j + \alpha_{0j} \cdot D_j \cdot P_{tj} + \alpha_{tj} \cdot D_j \cdot t P_{tj}\right). \qquad (6)$$

The coefficients on productivity interacted with the group dummies, α_{0j}, capture the difference in the initial signal's effect on starting wages for group j relative to those without referrals, while α_{tj} captures the difference in the effect of employer learning for that group.[15] If the signals employers receive

[15] I experimented with interactions with nonlinear functions of tenure that could provide better approximations of α_{Pj}; however, all such specifications appeared to ask too much of my relatively small sample.

when hiring workers using referral type j are more precise than the signals they receive when they have no referral, α_{0j} will be positive, while α_{tj} will be negative, reflecting the greater initial weight put on productivity and lower effect of learning for that group.

All regressions use wage levels, not logs.[16] The individual characteristics contained in X are a quartic polynomial in age, experience the employer considers relevant, dummy variables for education level, and missing value dummy variables for age, experience, and education. In specifications that do not use differences between workers in the same job, I control for differences in job characteristics by including establishment size, the percent of employees that are unionized, a missing value dummy for that percent, and dummy variables for occupation, industry and survey site.

There are two related problems with estimates from equations (5) and (6). The first is that wages are likely influenced by firm- or job-specific factors which the variables contained in the data can only proxy for. If the remaining job-specific components are correlated with productivity or referral types, the results from equations (5) and (6) will be biased.[17] Secondly, the results could also be biased if workers in different referral groups tend to sort into jobs that differ in their sensitivity to individual productivity. In that case, the wages of workers in jobs that were more sensitive to individual performance would put more weight

[16] This is more consistent with the model, which is in wage levels. Pinkston (2003) does the same thing. The results, however, are not qualitatively affected by this decision.

[17] Referrals from employees, friends and relatives of employers, and from other employers or unions, are positively correlated with wages even after controlling for individual and job characteristics (results not shown).

Devaro (2005) presents evidence suggesting that the tasks required by a job influence employer's choices of recruitment methods.

on both initial productivity and the information the employer learned about ability over time.[18]

Looking at the difference in wages between two workers in the same job eliminates the first problem and at least reduces the second. Differencing equation (5) or (6) is the only way to completely control for job-specific effects since all job-specific terms, observed or not, cancel out. Furthermore, since at least some of the identification in these differenced regressions comes from comparisons of workers that are in different referral groups, any additional bias that is caused by referral groups being correlated with the importance of individual ability to productivity in the job will be lessened.[19] My preferred specifications, therefore, will exploit the differences between the two workers.[20]

3 Results

Table 3 presents results from starting wage regressions. Again, if a type of referral is informative, the coefficient on its interaction with productivity should be significantly positive in these regressions. The first column presents results from a regression that pools all of the workers together instead of looking at the difference between workers in the same job. The second column presents results from a regression that exploits the difference between workers in the

[18] The larger concern in this case is not that this bias would replicate the effect of employers' having more precise information (because it doesn't), but that it would hide the effect in cases where a type of referral provided more precise information but was typically associated with a job that put little weight on individual performance.

[19] Roughly 60% of workers who were hired through a referral of some type are paired with a worker who did not receive the same type of referral.

[20] Another advantage to this approach is that it deals with the possibility that the productivity evaluations are relative to the expectations of the specific job.

same job. Estimates in the second column should not only be less biased by any association between referral type and job type, but comparing them to the estimates in the first column should give some idea of how the relationship of referral type to job type biases the results.

The results in Table 3 suggest that referrals from other firms or labor unions provide useful information that the employer would not have otherwise. When job characteristics are differenced out in column 2, the coefficient on the productivity evaluation interacted with a referral from another employer or a union is 0.0201 (0.0109), while the coefficient on productivity itself is only 0.0038 (0.0025). These results imply that a difference of one standard deviation in the productivity evaluation of a worker is associated with an hourly wage change of roughly \$0.72 if the worker was hired through a referral from another firm or union, while the same difference in productivity will only change the wage of a worker hired without a referral by a statistically insignificant \$0.11. The coefficients on other referral types interacted with the productivity evaluation in the wage difference regression are not statistically significant.

Although the effects of productivity on wages in the above regressions may seem small, there are reasons why we should not be surprised by their size. First, Bishop (1987) and Frazis and Loewenstein (2007) document that wages in this data set are compressed relative to productivity. As is discussed in Section 1, uncertainty about workers' true abilities, which exists even with informative referrals, reduces the effect of individual productivity on wages. Furthermore, the EOPP data used for this estimation contains relatively few workers in managerial, professional and technical occupations (8% of the sample) where wages are more correlated with individual productivity; and a relatively large number of workers in clerical or sales jobs (39%) and service occupations (19%)[21]. The results presented in this paper, therefore, might underestimate the value of referrals in the jobs where they matter most.

As is mentioned in Section 1, these starting wage results could be biased if the measure of initial productivity reflects what the employer thought at the time of interview about the worker's initial ability instead of what the employer thought at the time of hiring about the worker's ability. Since average tenure does vary across referral types, I examined this issue by estimating a simple wage difference regression that allowed the effect of the initial productivity measure on initial wages to vary by tenure. The results (not shown) provide no evidence that the effect of the initial productivity measure on initial wages varies by tenure, providing no reason to believe that differences in tenure across groups bias the starting wage results.

Even if there is not bias due to the effect of tenure on the initial productivity measure, there may still be problems with its use due to the fact that it is a retrospective measure. If employers' recollections are not precise or are biased in some way, the starting wage estimates presented above will be biased; however, estimates from current wage equations can produce both evidence of the importance of employer learning and an estimate of the effect of productivity

[21] The correlation of starting wage differences with initial productivity differences is 0.249 for the full sample with a significance level of 0.000; 0.299 (0.081) for professional, managerial and technical workers; 0.127 (0.218) for service occupations; and 0.134 (0.063) for clerical and sales jobs. A similar pattern is found when considering the correlation of current wages and current productivity.

on wages at the beginning of a job. Since the wage and productivity measures used in these regressions are either the current or the most recent measures at the time of interview, any bias in the results presented in Table 3 caused by the use of retrospective measures will be reduced in regressions of current wages on current productivity. Table 4 presents results from current wage regressions.

The estimated coefficients presented in Table 4a suggest that referrals from employees and other firms or unions provide employers with useful information. Significantly more weight is put on productivity initially for each of these referral types. The interaction of a referral from an employee with productivity has a coefficient of 0.0251 (0.0100) in column II, and the coefficient on a referral from another firm or labor union is 0.0297 (0.0087). Furthermore, employer learning has essentially no impact on the wages of these groups. The coefficient on Productivity $\times$ Tenure is 0.0007 (0.00006), while the coefficients on Productivity $\times$ Tenure interacted with having a referral from an employee is -0.0019 (0.0007) and that on the interaction with a referral from another firm or labor union is -0.0019 (0.0010).

Another interesting, and perhaps unexpected, result found in Table 4a is that referrals from the employers' friends and relatives appear to *reduce* the information the firm has relative to hiring with no referral at all. The coefficient on productivity interacted with such a referral is -0.0231 (0.0097) and that on productivity interacted with both tenure and a referral from the employer's friends or family is 0.0018 (0.0007). The coefficients are both statistically significant and have the opposite signs of what we would expect if this type of referral were informative. A possible explanation for this result is that the hiring of these workers involves favoritism that circumvents the firms' normal screening of applicants.[22]

Because the coefficients in Table 4a may be difficult to interpret, Table 4b presents differences in the effects of productivity on wages between each referral group and workers hired without a referral at various levels of tenure. At the time of hiring, a one-standard-deviation increase in productivity raises the wage of a worker referred by an employee by $0.50 more per hour than it would increase the wage of a worker hired without a referral. This same difference is almost $0.60 if the worker was referred by another firm or a labor union. This increase in productivity would raise the hourly wage of a worker referred by a friend or relative of the employer by $0.46 *less* than it would increase the wage of a worker hired with no referral at all.

These differences decrease over time as employers learn more about workers. Nonetheless, it takes roughly 13 months of tenure for an employer to learn as much about a worker hired without a referral as they knew about a worker who was referred by an employee at the time of hiring, and almost 16 months to learn as much as they knew about a worker referred by another firm or a union. It takes roughly a year for the apparent informational disadvantage of being referred by a friend or relative of the employer to dissipate.[23]

[22] Another result that is consistent with favoritism is that workers referred by friends or family of the employer are initially paid more than workers hired without a referral, but that this difference decreases over time. Evaluating the current wage regression from column II of Table 4a at average productivity for the full sample (77), these workers earn $0.41 more per hour when first hired but this difference disipates within a year.

[23] All of this analysis suffers from the use of linear interactions with tenure; however, interactions with a quadratic in tenure yield qualitatively similar results. Unfortunately, the

It is interesting to note that the coefficient on referrals from friends and family of the employer interacted with productivity decrease significantly between columns I and II of Table 4a. The coefficient on a referral from another firm or labor union interacted with productivity also decreases when job characteristics are differenced out, but not significantly. These differences are consistent with these referral types being associated with jobs that put more weight on individual productivity then other jobs do. To investigate this possibility further, I regressed current wages on individual characteristics, tenure and performance. I then replaced the worker's own referral type and its interactions with the referral type of the other worker in the same job and its interactions. The information an employer has about a worker's productivity should not be affected by the referral type of another worker, but any effect of a referral type being associated with a certain type of job should be picked up. The results (not shown) suggest that the other worker being referred by a friend or family member of the employer is associated with more weight being put on productivity.[24]

Finally, if referrals allow employers to more accurately evaluate job applicants, workers hired through these referrals should have higher productivity than workers hired without one. Although there are other reasons referrals and worker productivity might be related, I examine this relationship in Table 5, which presents results from regressions on the difference in current productivity between workers in the same job.[25] The second column allows the effect of a

quadratic and other more flexible specifications appear to ask too much of this relatively small data set.

[24] This result holds even when I exclude observations in which the two workers had the same referral type.

[25] I use differences in current productivity because productivity evaluations may be relative

referral on productivity to vary with tenure, while column I does not.[26]

The results presented in Table 5 suggest that workers hired through referrals from employees and other firms or labor unions have higher productivity than similar workers hired with no referrals.[27] In the first column, the coefficients on referrals from employees and from other firms or labor unions are large and significantly positive at 7.32 (3.28) and 14.95 (6.56), respectively. The coefficient on employee referrals changes very little in column II, but its standard error increases. The coefficient on a referral from another firm or a labor union is larger at 22.55 (8.39), but this positive effect decreases with tenure. The coefficient on the interaction of tenure with referrals from employers or unions is -0.77 (0.34).

4 Discussion

The evidence presented in this paper suggests that referrals from current employees, other firms and labor unions provide employers with more information about job applicants than they would have otherwise. Evaluations of a worker's productivity have a larger (more positive) effect on wages at the time of hiring for these groups than for workers who where hired without a referral. Furthermore, employer learning has less of an effect on the wages of workers referred by employees, or by other firms or unions. Curiously, I find evidence that em-

to the expectations of the job and the current productivity measure should be more reliable than the retrospective starting performance measure.

[26] The regressions presented in each column control for the same variables used in regressions on current wage differences.

[27] These results confirm results in Holzer (1987), which do not look at differences between workers in the same firm.

ployers obtain *less* information at the time of hiring about workers who were referred by friends and relatives of the employer than they would collect without a referral, which is consistent with favoritism allowing these workers to be hired with less scrutiny than other applicants might receive. I find no evidence that referrals from other sources (schools, community groups, etc.) provide useful information.

Because the data used in this paper provide information on two workers in the same job for a subset of firms, I am able to reduce bias caused by different types of referrals being associated with different types of jobs. My analysis supports previous work in this literature that suggests this bias could be important. I find that referrals from the employer's friends and relatives are associated with jobs that base wages more on worker productivity than jobs that are associated with no referral do.

The finding that referrals from employees, other firms and labor unions provide employers with more information than other hiring channels do is consistent with earlier results in the literature. For example, Holzer (1988) and Blau and Robins (1990) find that referrals from a worker's friends and family are more effective than other search methods when it comes to producing offers and acceptances. Applying the statistical discrimination model of Cornell and Welch (1996), employers having more precise information about applicants with these types of referrals could explain the higher rate of offers these referrals generate, even if the average productivity of applicants does not vary by recruiting method. The variance of expected productivity conditional on a signal is higher the more precise that signal is, which makes it more likely that the worker with highest conditional expectation in a pool of applicants is from the group with the most precise signal.

A related argument could be made for why workers who received referrals from these sources have higher productivity, as reported by Holzer (1987) and this paper. Employers are likely to hire workers who are more productive on average when their information about the ability of applicants is more precise. Of course, workers hired through such referrals might also be more productive because they are drawn from a pool of applicants that is more productive on average, because the people who referred them exert peer pressure, or for some other reason. Sorting out the degree to which employers' having more precise information actually affects hiring, worker productivity and other outcomes remains for future research.

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Table 1. Summary Statistics

	Mean	Std Dev.	Number of Obs.
Initial Wage	4.710	2.165	1041
Current Wage	5.462	2.557	1032
Initial Productivity	53.078	25.747	1052
Current Productivity	77.264	20.058	1052
High School	0.614	0.487	1005
Some College	0.195	0.396	1005
College	0.055	0.228	1005
Age	25.879	8.922	1019
Relevant Experience	43.907	58.016	546
Tenure	10.697	8.233	992
Establishment Size	123.747	892.500	1052
Prof., Man., Tech.	0.076	0.265	1052
Service	0.190	0.393	1052
Clerical and Sales	0.388	0.487	1052
Machine Work	0.135	0.342	1052
Bench Work	0.023	0.149	1052
Structural Work	0.082	0.274	1052
Referral Source:			
Employee	0.259	0.438	1052
Employer's Friend	0.064	0.244	1052
Other Firm/Union	0.056	0.230	1052
Other Source	0.181	0.385	1052
No Referral	0.441	0.497	1052

Notes: Sample limited to observations with non-missing values of initial or current wage. Relevant Experience and Tenure measured in months.

Table 2. Summary Statistics by Referral Source

	Employee	Employer's Friend/Family	Other Firm or Labor Union	Other Source	No Referral
Initial Wage	4.653	4.883	6.798	4.230	4.652
	(0.117)	(0.280)	(0.548)	(0.127)	(0.090)
Current Wage	5.429	5.894	8.118	4.777	5.357
	(0.145)	(0.384)	(0.616)	(0.145)	(0.101)
Initial Productivity	53.107	60.701	64.203	46.516	53.233
	(1.601)	(2.616)	(3.092)	(1.887)	(1.177)
Current Productivity	77.665	81.343	81.831	74.805	76.866
	(1.167)	(1.792)	(2.622)	(1.627)	(0.931)
High School	0.630	0.590	0.673	0.541	0.630
	(0.030)	(0.063)	(0.064)	(0.037)	(0.023)
Some College	0.191	0.180	0.145	0.199	0.204
	(0.024)	(0.050)	(0.048)	(0.030)	(0.019)
College	0.053	0.066	0.036	0.066	0.052
	(0.014)	(0.032)	(0.025)	(0.019)	(0.010)
Age	25.606	25.092	28.621	24.122	26.543
	(0.586)	(0.929)	(1.353)	(0.556)	(0.424)
Relevant Experience	41.344	38.415	63.325	29.891	48.257
	(4.123)	(6.587)	(10.989)	(4.069)	(4.329)
Tenure	12.357	11.768	10.792	11.157	9.899
	(0.587)	(1.272)	(1.153)	(0.634)	(0.363)
Establishment Size	57.820	43.433	89.983	108.368	184.582
	(14.618)	(11.917)	(19.722)	(22.955)	(60.913)
Prof., Man., Tech.	0.118	0.104	0.085	0.058	0.054
	(0.020)	(0.038)	(0.037)	(0.017)	(0.010)
Service	0.184	0.299	0.051	0.179	0.200
	(0.024)	(0.056)	(0.029)	(0.028)	(0.019)
Clerical and Sales	0.349	0.299	0.390	0.453	0.397
	(0.029)	(0.056)	(0.064)	(0.036)	(0.023)
Machine Work	0.107	0.179	0.102	0.111	0.159
	(0.019)	(0.047)	(0.040)	(0.023)	(0.017)
Bench Work	0.004	0.015	0.034	0.026	0.032
	(0.004)	(0.015)	(0.024)	(0.012)	(0.008)
Structural Work	0.096	0.090	0.153	0.058	0.073
	(0.018)	(0.035)	(0.047)	(0.017)	(0.012)
Starting Wage Obs.	269	65	58	189	460
Current Wage Obs.	265	64	59	187	457

Notes: Standard errors are in parentheses. Sample limited to observations with non-missing values of initial or current wage.
Relevant Experience and Tenure measured in months.

Table 3. Starting Wage Regressions

	I Pooled Regressions	II Wage Differences
Employee Referral	0.2377 (0.4257)	0.1479 (0.2093)
Employer's Frnd/Fam	0.8175 (0.6078)	0.0828 (0.2540)
Firm/Union Referral	-2.7883 (1.1027)	-0.7122 (0.5767)
Other Referral	-0.1759 (0.4840)	-0.0168 (0.2086)
Productivity	0.0069 (0.0062)	0.0038 (0.0025)
Prod. x Employee Ref.	-0.0008 (0.0089)	-0.0033 (0.0047)
Prod. x Employer Ref.	-0.0113 (0.0103)	-0.0036 (0.0058)
Prod. x Firm/Union Ref.	0.0578 (0.0276)	0.0201 (0.0109)
Prod. x Other Ref.	0.0029 (0.0099)	0.0018 (0.0043)
Observations	992	496 worker pairs

Notes: Standard errors (in parentheses) are Huber/White allowing for dependence within survey site. The regression in column I also includes a quartic polynomial in age, a dummy for age missing, dummy variables for gender and education, relevant experience and its missing value dummy. The job characteristics in column I are dummy variables for survey site, occupation and industry, as well as number of employees in the establishment, the percent that are unionized and its missing-value dummy variable. The regression in column II controls for differences in the individual characteristics controlled for in column I.

Table 4a. Current Wage Regressions

	I Pooled Regressions	II Wage Differences
Employee Referral	-0.9330 (1.4254)	-2.1480 (0.7109)
Employer's Frnd/Fam	-2.9358 (1.3155)	2.1849 (0.7726)
Firm/Union Referral	-5.3842 (3.2247)	-1.8551 (0.7967)
Other Referral	-2.5418 (0.8529)	-0.4350 (0.7161)
Productivity	-0.0060 (0.0086)	0.0044 (0.0046)
Productivity x Tenure	0.0012 (0.0007)	0.0007 (0.0006)
Prod. x Employee Ref.	0.0215 (0.0174)	0.0251 (0.0100)
Prod. x Employer Ref.	0.0537 (0.0194)	-0.0231 (0.0097)
Prod. x Firm/Union Ref.	0.0658 (0.0367)	0.0297 (0.0087)
Prod. x Other Ref.	0.0378 (0.0099)	0.0060 (0.0101)
Prod x Tenure x Employee Ref.	-0.0021 (0.0014)	-0.0019 (0.0007)
Prod x Tenure x Employer Ref.	-0.0001 (0.0022)	0.0018 (0.0007)
Prod x Tenure x Firm/Union Ref.	-0.0063 (0.0038)	-0.0019 (0.0010)
Prod x Tenure x Other Ref.	-0.0019 (0.0009)	-0.0005 (0.0007)
Observations	958	479 worker pairs

Notes: Standard errors (in parentheses) are Huber/White allowing for dependence within survey site. The regression in column I also includes a quartic polynomial in age, a dummy for age missing, dummy variables for gender and education level, relevant experience and its missing value dummy, tenure, a missing value dummy for tenure, and all appropriate interactions of that missing value dummy. The job characteristics in column I are dummy variables for survey site, occupation and industry, as well as number of employees in the establishment, the percent that are unionized and a missing value dummy variable for the percent unionized. The regression in column II controls for differences in the variables controlled for in column I.

Table 4b. Current Wage Regressions: Differences in Effects of a One Standard Deviation Increase in Productivity on Wages.

	Employee	Employer's Friend or Family	Other Firm or Labor Union	Other Referral Sources
Tenure = 0 months	0.5021 (0.1996)	-0.4622 (0.1940)	0.5950 (0.1733)	0.1191 (0.2013)
Tenure = 6 months	0.2744 (0.1443)	-0.2462 (0.1331)	0.3726 (0.0876)	0.0606 (0.1383)
Tenure = 12 months	0.0466 (0.1310)	-0.0303 (0.1118)	0.1503 (0.1184)	0.0021 (0.1180)
Tenure = 18 months	-0.1811 (0.1698)	0.1857 (0.1484)	-0.0721 (0.2215)	-0.0564 (0.1577)

Notes: Effects are calculated using the regression presented in column II of Table 4a. All effects are relative to those for workers hired without a referral. A one standard deviation increase in productivity is rounded to 20.

Table 5. Effects of Referrals on Current Productivity

	I	II
Employee Referral	7.322 (3.281)	8.918 (5.741)
Employer's Frnd/Fam	4.296 (4.520)	0.935 (8.158)
Firm/Union Referral	14.949 (6.561)	22.554 (8.390)
Other Referral	0.481 (4.884)	5.123 (6.019)
Tenure	0.307 (0.139)	0.495 (0.217)
Employee Referral x Tenure	…..	-0.146 (0.407)
Employer's Frnd/Fam x Tenure	…..	0.216 (0.448)
Firm/Union Referral x Tenure	…..	-0.766 (0.336)
Other Referral x Tenure	…..	-0.387 (0.466)
Observations	533 worker pairs	533 worker pairs

Notes: Standard errors (in parentheses) are Huber/White allowing for dependence within survey site. Regressions control for differences in a quartic age polynomial, age's missing value dummy, gender, relevant experience, its missing value dummy, a dummy variable for each worker equal to one if that worker attained a higher level of education than the other, a missing value dummy variable for tenure, and the appropriate interactions of that missing value dummy.