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 either collecting less information than they would otherwise or ignoring information. 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 hired without a referral 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 explanation for the previous literature's observations about referrals is that referrals allow firms to select from a pool of more capable applicants.[1] Kugler (2003) and others have suggested that referred workers might also be preferred by some employers because the employee who referred them can exert some peer pressure.[2] 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.[3] 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

[1] For example, Saloner (1985) develops a model in which referrers only refer those who are most likely to be of higher ability. Montgomery (1991) suggests that employee referrals might alleviate adverse selection involved in hiring, benefiting both well-connected workers and the firms that hire through referrals.

[2] This is consistent with Castilla (2005) finding that increases in performance associated with referrals in a call center is contingent on the referrer staying with the firm.

[3] Shinnar, et al (2004) suggest that even the act of referring a job applicant can improve a referring worker's attitude toward the firm.

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 worry that the empirical results of Simon and Warner (1992) might be driven by factors other than the informational content of referrals. 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.[4] Finally, their estimates do little to 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).[5,6]

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). More importantly, the tested predictions can be distinguished from effects of group differences in average productivity, and from effects of favoritism. Furthermore, the data used in this paper includes

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

[5] The sample Simon and Warner (1992) use may alleviate this problem; however, 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 unobserved qualities.

[6] Kugler (2003) develops a model of dual labor markets in which "good" jobs are sensitive to individual performance and require a referral. Devaro (2005) documents associations between skill requirements and other job characteristics and the firm's choice of recruiting method.

information on two workers in the same job, which allows me to cancel out differences in job and firm characteristics.

The estimation results are 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, I find evidence that suggests hiring through friends or relatives of the employer involves favoritism that results in employers' either collecting less information than they would otherwise or ignoring information when setting wages. I find no evidence that referrals from schools, community organizations or other sources provide any useful information.

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 used in this paper. Section 3 discusses estimation, as well as issues such as favoritism and unobserved job characteristics. Section 4 presents estimation results, and Section 5 concludes.

1 Wages with Noisy Productivity Signals

The 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 implications are the same:

1. 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

2. The more accurate initial information is 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 worker i's productivity, $\varepsilon_{ij} \sim N\left(0, \sigma^2_{\varepsilon j}\right)$ and $\sigma^2_{\varepsilon j}$ varies by referral type j. This signal can include 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. As that information becomes more (or less) reliable, $\sigma^2_{\varepsilon j}$ decreases (increases).

Assume the employer also observes a vector of worker characteristics X_i and initial productivity is a known linear function of X_i and an error term:

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

where β is common knowledge and σ^2_ν is the same for all groups. The initial signal can then be used to predict the part of a worker's productivity that is not already explained by education and other easily-observed characteristics.

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.[7] As a result, the empirical results of this paper cannot be explained by referred workers being more capable, or performing better due to peer pressure.

Of course, we do not observe the initial signal s_{ij} in the data.[8] 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 that the evaluation of productivity at t is

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

where S_{tj} is an unbiased 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

[7] This is a simple generalization of the model in Aigner and Cain (1977), which assumed that the variance of μ_{0i} did not differ between groups.

[8] 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.

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 $\sigma^2_{\varepsilon j}$.[9] 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 or time since the worker was hired, but these sources of bias can (and will) be examined empirically.[10]

Assuming wages at tenure t are equal to expected productivity conditional on observed characteristics and P_t, we can write

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

The coefficient α_{Pj} increases in tenure as employers learn and P_{tj} becomes more precise; however, it increases more slowly the more precise initial information is. In other words, the more information the employer had initially, the less

[9] 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.

[10] If the evaluation of initial productivity is actually S_{tj}, as it is in equation (3), the bias varies by tenure as observations of the workers performance on the job make the employer's information more precise. If the error is instead due to the retrospective nature of the initial performance measure, the bias will vary by the amount of time that has passed since the worker started at the firm. Both of these possibilities are discussed in Section 4.

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).[11]

2 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.[12] 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 establishments were asked for information about the last worker hired, including evaluations of the worker's current productivity and productivity in the first two weeks on the job. Only the 1982 survey contains the information on recruiting 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.[13] Differencing two workers in the same

[11] This assumes 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.

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

[13] 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 occupa-

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 consistency, I restrict all estimates to this subsample even when those estimates do not use the difference between the two workers; however, non-differenced results in the full sample (not shown) are qualitatively similar to those from the restricted sample.[14]

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.[15] 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.[16] I use the first and last of these evaluations and refer to them as "initial productivity" and "current

tion 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 \$0.15 in nominal wages and \$0.23 in constant 1982 dollars. 90 percent differ by \$1.15 or less in nominal terms and \$1.59 or less in 1982 dollars.

[14] 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. When a dummy variable for the worker being the second worker is included in wage regressions, the coefficient is always small and statisticaly insignificant. Non-differenced results that used the full sample (not shown) are qualitatively similar to those from the restricted sample.

[15] The interviewer asks to speak with the person responsible for hiring in each establishment. I assume, as does the survey, that this person also has sufficient information to judge the workers' productivity on the job.

[16] 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.

When a dummy variable for the worker staying is added to regressions, its coefficient is not statistically significant and other results do not change. Limiting attention to cases in which neither worker left produces qualitatively similar results, but standard errors are much higher due to the smaller sample size.

productivity", respectively.

The data also contain questions about how the worker was hired; i.e., using a newspaper ad, a referral from a current employee, etc. These questions identify several sources of referrals that are mutually exclusive in the data. Since the source likely affects how informative a referral 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.[17]

Limiting attention to establishments that report at least some information on two workers leaves 659 establishments (and worker pairs). I then drop 46 worker pairs in which the workers' pay is based on commission, tips or a piece-rate scale; 13 pairs in which one worker's start date was more than 4 years before the interview date; 37 pairs in which tenure is not reported and cannot be calculated because start date is not reported; and two pairs in which one worker was younger than 16.[18] Finally, two pairs are excluded because they appear unlikely to have been hired for the same job.[19] The resulting sample has

[17] 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. "Other" referrals come from schools, employment agencies, community organizations, etc. Preliminary estimation that separated each of these groups into more specific referral types suggested that the component types behave similarly. Intuitively, one might think of other firms and unions as professional connections that might have observed the worker on a job, while "other" referrals come from organizations that might be trying to place low-skilled workers.

[18] 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. These workers are more productive, and the correlation of their wages with performance is twice as large as other workers.

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.

Preliminary estimation obtained qualitatively similar results without these restrictions.

[19] Their starting wages differ by over $10 per hour, their ages differ by 23 or more years,

roughly 500 worker pairs and 1000 individual workers. All tables that present estimates also present the number of observations used.

Table 1 presents summary statistics for the sample. The average starting wage is $5.17 (in 1982 dollars) and the average current wage is $5.50. The average worker has 10.8 months tenure with the employer, and almost 43 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. About 45% of the sample of 981 workers had no referral, 25% 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 19% 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 243 workers who were referred by an employee of the company, 58 referred by a friend or family member of the employer, 54 referred by another employer or a labor union, and 182 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 slightly lower. The average worker who was referred by a friend or relative of the employer works in an

and their relevant experience differs by almost 20 years.

establishment of 48 workers, while the average worker who was hired without a referral is in an establishment with 192 workers.[20] 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.[21] Workers referred by other firms or labor unions are less likely than other workers to be in service occupations.

Finally, it should be noted that this survey is over two decades old, and we should be cautious about generalizing results to more recent labor markets. Nonetheless, the 1982 EOPP survey currently provides a unique opportunity to study referrals, and more recent evidence suggests referrals are still an important part of hiring and job search. Holzer (1996) finds similar percentages of workers being hired through referrals in data collected between 1992 and 1994.[22] Using more recent data, Marmaros and Sacerdote (2002) and Mayer (2010) present evidence that social networks play an important role in the labor market outcomes of recent college graduates.[23] Finally, a simple comparison of data on job search methods used by respondents in the 2007 wave of the NLSY97 to methods used by respondents in the 1986 wave of the NLSY79 suggests that the

[20] 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.

[21] Bench work occupations involve the fabrication, assembly or repair of various products. Examples include wood working, watch repair, and fabricating medical prosthetics.

[22] 25-26% were referred by current employees; 13-15% by the sum of unions, the employers' acquaintances, etc.; and 13-18% by employment services, community groups and schools. The data he used came from the Multi-City Study of Urban Inequality, which would not allow a comparision of two workers in the same job. The ranges in estimates depend on the subsample used.

[23] Marmaros and Sacerdote (2002) examine the use of social networks among the Dartmouth College class of 2001 to obtain their first jobs. Mayer (2010) finds evidence that social connections through Facebook.com positively affect the job prospects of students who graduated from Texas A&M between 2005 and 2008.

use of friends and family has, if anything, increased over the past two decades.[24]

3 Estimation and Alternative Explanations

In all of the estimation that follows, data from the different referral groups are pooled together.[25] Regressions based on equation (3) take the form

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

where D_j are dummy variables for referral group (the omitted group is those with no referral); S_{tj} is the employer's evaluation of the worker's initial productivity; and X controls for observed characteristics, including 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. *If referrals of type j are informative, α_j should be positive.*

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

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

The coefficients on productivity interacted with the group dummies, α_{0j}, cap-

[24] Each survey asks a series of questions about job search methods used during the respondents' most recent unemployment spells. Limiting each sample to workers who were 22-28 years old, I found that roughly 41% contacted friends and family in 1986, while almost 54% contacted friends and family in 2007. I leave a more detailed analysis of how job search methods have changed over time to future research.

[25] Due to the sample size and the number of groups (five instead of two) it is not practical to run separate regressions for each group. Furthermore, pooling groups together makes comparisons to differenced regressions, which are the focus of this paper, easier.

ture 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.[26] *If the signals employers receive when hiring workers through referral type j are informative, α_{0j} will be positive, and α_{tj} will be negative.* This reflects the greater initial weight put on productivity and lower effect of learning for that referral type.

All regressions use wage levels, not logs.[27] The individual characteristics contained in X are gender, 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.

3.1 Favoritism and Social Networks

The effects of favoritism are easily separated from results based on equations (5) and (6). The coefficients on the dummy variables for referral type, γ_j, will capture any initial premium paid to workers who have certain connections. If such a premium then decreases with tenure, which would be consistent with Simon and Warner (1992), the coefficient on that referral type interacted with

[26] 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, resulting in larger standard errors.

[27] 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.

tenure in equation (6), γ_{tj}, will reflect that decrease.

Favoritism is not likely to bias any of the coefficients on performance evaluations unless it causes the employer to bypass normal screening procedures when hiring a worker, or results in hiring and wage decisions being made regardless of any information on productivity. In those cases, favoritism would have the opposite effect on the correlation between wages and productivity evaluations as an informative referral. A referral type that involved favoritism might initially appear to provide *less* information about the worker, and employer learning would have a greater effect on later wages.[28] In other words, α_j in equation (5) and α_{0j} in (6) would be negative, and α_{tj} in equation (6) would be positive.

It's also possible that a worker who is capable of getting a referral to the employer in the survey has better social networks than workers without referrals, and they might receive more (and better) outside offers as a result. In models of asymmetric employer learning, firms often pay workers less than the workers' expected productivity because competition is limited by other firms knowing less about the worker than the current employer does.[29] Pinkston (2009) shows that, if outside employers are capable of collecting private signals (through interviews, for example), competition can cause wages to converge to the employer's conditional expectation despite the current employer having more precise information.

[28] Assuming that the effects of favoritism dissipated over time, which would be required if it were to explain the results of Simon and Warner (1992). A declining effect of favoritism could be explained by the favored worker increasingly being compared to coworkers that the employer is more familiar with (and perhaps fond of).

[29] Gibbons and Waldman (1999) provide a survey of this literature. For two examples, see Waldman (1984) and Scoones and Bernhardt (1998).

Therefore, if workers hired through certain referrals tend have better social networks, and better networks produce more outside offers, wages might be more correlated with productivity for those referral types even if the referrals are not informative. In contrast to the predictions I test, this would imply that the correlation of wages and productivity would increase faster with tenure for referral types that are associated with better social networks because increased competition from outside firms would cause wages to more quickly converge to the employer's expectation. Furthermore, this increase in competition would imply a higher quit rate for those referral types, which does not fit the data.[30]

3.2 Unobserved Job Characteristics

As was mentioned in previous sections, there is reason to worry that some referral types might be associated with unobserved job characteristics. To model this in a simple manner, we can add an unobserved firm- or job-specific term to equations (5) and (6):

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

$$w_{tj} = X\beta_{tj} + \alpha_0 P_{tj} + \alpha_t t P_{tj} + \sum_j \begin{pmatrix} \gamma_j D_j + \gamma_{tj} t D_j + \\ \alpha_{0j} D_j P_{tj} + \alpha_{tj} t D_j P_{tj} \end{pmatrix} + e_f \quad (6')$$

The possibility that e_f is correlated with referral types suggests that any of the coefficients on referral dummy variables or their interactions could suffer from omitted variable bias. Productivity evaluations might also be correlated with

[30] Holzer (1987) finds that workers referred by an employee are more likely to still be employed by the firm at the time of interview. In my own regressions (not shown), I do not find a statistically significant relationship, but the results are qualitatively similar to Holzer's.

e_f if they are relative to the expectations of the specific job, introducing further bias.

Having data on two workers in the same job allows us to cancel out any firm- or job-specific variables by considering differences between the two workers. Given two workers, $i = 1, 2$, the difference in starting wages is

$$\Delta w_0 = \Delta X\beta + \alpha \Delta S_{tj} + \sum_j \left[\gamma_j \Delta D_j + \alpha_j \left(D_{1j} S_1 - D_{2j} S_2\right)\right] + \Delta\phi, \quad (7)$$

where D_{ij} are the dummy variables for worker i having referral type j, and S_i are the evaluations of worker i. The difference in current wages is

$$\begin{aligned} \Delta w_t &= \Delta X\beta_{tj} + \alpha_0 \Delta P_t + \alpha_t \left(t_1 P_{t1} - t_2 P_{t2}\right) \\ &\quad + \sum_j \begin{bmatrix} \gamma_j \Delta D_j + \gamma_{tj} \left(t_1 D_{1j} - t_2 D_{2j}\right) \\ +\alpha_{0j} \left(D_{1j} P_{t1} - D_{2j} P_{t2}\right) \\ +\alpha_{tj} \left(t_1 D_{1j} P_{t1} - t_2 D_{2j} P_{t2}\right) \end{bmatrix}. \end{aligned} \quad (8)$$

In both cases, any firm- or job-specific characteristics in X or the error term cancel out, eliminating potential bias due to unobserved job characteristics.[31]

A more difficult problem comes from the possibility that firms do not simply pay workers wages equal to expect productivity, and that there is heterogeneity across firms in the degree to which wages are correlated with productivity. This sort of heterogeneity would not cancel out when two workers in the same job are compared.[32] If some referral types are associated with jobs that put more weight on individual productivity when setting wages, as suggested by

[31] Equations (7) and (8) differ from their counterparts in Pinkston (2003) due primarily to the use of a comparison group, workers hired without a referral. Pinkston (2003) estimated a separate coefficient for each of two groups, male and female.

[32] If, for example, firms put less weight on their evaluations of a worker's productivity when the market for that worker's skills was less competitive, equation (7) might instead take the

Kugler (2003), both the initial effect of productivity on wages and the later effects of employer learning will be larger for those groups.[33] Problems due to referrals being associated with jobs that put more or less weight on performance should be reduced by differencing, as some of the identification will come from jobs where the two workers have different referral types, but it will not be eliminated.[34] In Section 4, I consider the degree to which the main results appear consistent with an association between referral type and the correlation of wages and productivity, along with other evidence that might suggest such an association.

4 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 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

form

$$\Delta w_0 = \Delta X\beta + b_f \alpha \Delta S_{tj} + \sum_j \left[\gamma_j \Delta D_j + b_f \alpha_j \left(D_{1j} S_1 - D_{2j} S_2\right)\right] + \Delta\phi,$$

where $b_f \in [0, 1]$ varies by firm and job.

[33] This bias would not replicate the effect of employers' having more precise information, but it might 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.

[34] 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.

estimates in the first column should give some idea of how the relationship of referral type to job type biases the results.

Before considering differences by referral type, note that what seems like small effects of productivity overall in Table 3 should not be surprising. Previous work by Bishop (1987) and Frazis and Loewenstein (2007) documented 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 correlation of individual productivity and wages. Furthermore, over half the workers in the data used for this estimation are in clerical or sales jobs (39%) and service occupations (17%) where the correlation between wages and productivity is the weakest[35]. The results presented in this paper, therefore, might underestimate the value of referrals in the jobs where they matter most.

The only result in Table 3 that is consistent with a type of referral being informative comes from the regression in column I, which does not difference out job characteristics. The coefficient on productivity interacted with a referral from another firm or a labor union is 0.072 (0.039). When two workers in the same job are compared in column II, all of the interactions of referral type and productivity have negative coefficients, with the coefficient on productivity interacted with a referral from an employee of the firm having a statistically significant coefficient of -0.0167 (0.0083).

It is important to remember that the estimates in Table 3 rely on retro-

[35] The correlation of initial wage and initial productivity is -0.095 for workers in clerical, sales or service occupations; and 0.309 for all other workers. For current wages and productivity the corresponding correlations are 0.05 and 0.196.

spective measures of wage and productivity. The employers' assessments of workers' productivity in the first two weeks on the job may be biased by later observations of performance, or it may become more prone to error as workers' first weeks become more distant. I find evidence (not shown) that supports this later source of bias: The measure of initial productivity is less correlated with initial wages the further the worker's start date is in the past,[36] and the average start date of workers hired through employee referrals is over two months before the average for workers hired without a referral.[37]

Given the likely bias in regressions of initial wages on initial productivity evaluations, my preferred estimates rely on current wages and productivity measures. Fortunately, estimates from current wage equations can produce both evidence of the importance of employer learning and an estimate of the effect of 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.

[36] I regressed the differences in wages on differences in a quartic polynomial in time since the start date, initial productivity, and productivity interacted with the polynomial. The effect of the productivity evaluation on initial wages is not statistically significant from zero if the worker began more than a year ago.

[37] The average worker hired through an employee referral was hired 14.2 months before the interview. The average without a referral is 11.9 months. This difference is roughly one month even when comparing two workers in the same job.

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 0.0196 (0.0101) in column II, and the coefficient on a referral from another firm or labor union is 0.0266 (0.0155). Furthermore, the coefficients on Productivity $\times$ Tenure interacted with having a referral from an employee is -0.0015 (0.0007) and that on the interaction with a referral from another firm or labor union is -0.0016 (0.0022). While only the coefficient on the interaction with a referral from an employee is statistically significant, both of these effects are of the expected sign.

Table 4a also presents evidence that is consistent with referrals from the employers' friends and relatives involving favoritism that allows these workers to bypass the firm's usual screening or wage-setting practices. The coefficient on productivity interacted with such a referral is -0.0278 (0.0120) and that on productivity interacted with both tenure and a referral from the employer's friends or family is 0.0021 (0.0009). The coefficients are both statistically significant and have the opposite signs of what we would expect if this type of referral were informative.

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 \$0.39 more per hour than it would increase the wage of a worker hired without a referral. This difference is almost

$0.53 if the worker was referred by another firm or a labor union. On the other hand, this increase in productivity would raise the hourly wage of a worker referred by a friend or relative of the employer by almost $0.56 *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 a year 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 17 months to learn as much as they knew about a worker referred by another firm or a union. It takes nearly 13 months for the apparent informational disadvantage of being referred by a friend or relative of the employer to dissipate.[38]

As was mentioned above, the results that appear to suggest referrals from the employer's friends and family members are less informative than no referral at all are consistent with favoritism. These workers might be hired without being subjected to the firm's usual screening methods, or their initial wages might be set without regard to their expected productivity. Providing further evidence of favoritism, the results in Table 4c show that workers referred by friends or family of the employer are initially paid $0.52 more per hour than workers hired without a referral, but this difference dissipates in roughly one year.[39] This is the same pattern of wages described by Simon and Warner

[38] All of this analysis uses linear interactions with tenure; however, interactions with a quadratic in tenure yield qualitatively similar results. Unfortunately, standard errors in the quadratic and other nonlinear specifications are too large to see statistically significant effects, probably due to the small sample size.

[39] These difference in effects of referrals on wages are calculated at average productivity, which is rounded to 77.

(1992). In contrast, there is no such wage effect of a referral from an employee of the firm; and the positive effect of referrals from other firms or labor unions appears to be constant over time, which could suggest higher unobserved human capital for this group.[40]

Looking back at Table 4a, the importance of differencing two workers in the same job is made clear by comparing columns I and II. The coefficient on referrals from friends and family of the employer interacted with productivity decreases significantly between columns. The coefficient on a referral from another firm or labor union interacted with productivity also decreases when job characteristics are differenced out, but the change is not statistically significant. These differences are consistent with these referral types either being associated with unobserved job characteristics, or with jobs that put more weight on individual productivity than 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) support the finding that the other worker being referred by a friend or family member of the employer is associated with more weight being put on productivity.[41]

[40] Workers referred by a union, for example, might have training that is not reflected in the data, but is captured by the dummy variable for that referral type.

[41] This result holds even when I exclude observations in which the two workers had the

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 of the difference in current productivity between workers in the same job.[42] The second column allows the effect of a referral on productivity to vary with tenure, while column I does not.[43]

The results in Table 5 suggest that workers hired through referrals from employees and from other firms or labor unions have higher productivity than similar workers hired with no referrals.[44] In the first column, the coefficients on referrals from employees and from other firms or labor unions are large and statistically significant at 8.16 (3.62) and 14.84 (6.94), 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 22.19 (8.04), but this positive effect decreases with tenure. The coefficient on the interaction of tenure with referrals from employers or unions is -0.79 (0.32). There is no evidence that referrals from the employer's friends or relatives are associated with higher productivity, further supporting the idea

same referral type. I also found evidence consistent with referrals from other firms and unions being associated with jobs that put more weight on performance; however, that result was not statistically significant when I excluded observations in which both workers had the same referral type.

[42] I use differences in current productivity because productivity evaluations may be relative to the expectations of the job and the current productivity measure should be more reliable than the retrospective starting performance measure.

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

[44] These results confirm results in Holzer (1987) that do not look at differences between workers in the same job.

that these referrals might involve some favoritism.

5 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.

In contrast, my results appear to suggest that employers 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. This result is consistent with favoritism allowing these workers to be hired with less scrutiny than other applicants might receive, or with information simply being ignored when their wages are set. Providing further evidence of favoritism, I find that referrals from friends or family of the employer are unique in that they don't on average result in hiring more productive workers, but they are associated with a wage premium that declines with tenure on the job.

Finding that referrals from employees, other firms and labor unions provide employers with more information than other hiring channels 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. 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. Even if employers eventually learn everything about any worker they hire, workers with informative referrals will have an advantage in the hiring process.

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	5.173	2.442	971
Current Wage	5.505	2.550	964
Initial Productivity	53.078	25.747	981
Current Productivity	77.004	20.077	981
High School	0.613	0.487	937
Some College	0.197	0.398	937
College	0.053	0.225	937
Age	25.871	8.905	956
Female	0.456	0.498	981
Relevant Experience	42.828	57.228	511
Tenure	10.766	8.240	981
Establishment Size	130.123	923.822	981
Prof., Man., Tech.	0.077	0.267	981
Service	0.179	0.384	981
Clerical and Sales	0.392	0.489	981
Machine Work	0.135	0.341	981
Bench Work	0.024	0.155	981
Structural Work	0.080	0.271	981
Referral Source:			
Employee	0.251	0.434	981
Employer's Friend	0.060	0.238	981
Other Firm/Union	0.055	0.228	981
Other Source	0.187	0.390	981
No Referral	0.448	0.497	981

Notes: The sample is limited to observations used in current or starting wage regressions.
Relevant Experience and Tenure are 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	5.285	5.415	7.305	4.719	5.008
	(0.150)	(0.327)	(0.668)	(0.154)	(0.098)
Current Wage	5.561	5.992	7.955	4.913	5.350
	(0.157)	(0.423)	(0.647)	(0.153)	(0.101)
Initial Productivity	52.622	59.322	64.315	46.109	53.383
	(1.677)	(2.815)	(3.242)	(1.939)	(1.224)
Current Productivity	77.524	81.237	82.278	74.333	76.608
	(1.200)	(1.915)	(2.474)	(1.677)	(0.969)
High School	0.631	0.611	0.660	0.534	0.629
	(0.031)	(0.067)	(0.068)	(0.038)	(0.024)
Some College	0.199	0.167	0.160	0.201	0.203
	(0.026)	(0.051)	(0.052)	(0.030)	(0.020)
College	0.051	0.074	0.040	0.069	0.047
	(0.014)	(0.036)	(0.028)	(0.019)	(0.010)
Age	25.692	24.456	28.358	24.236	26.554
	(0.608)	(0.903)	(1.425)	(0.568)	(0.439)
Female	0.439	0.441	0.389	0.492	0.460
	(0.032)	(0.065)	(0.067)	(0.037)	(0.024)
Relevant Experience	41.581	34.886	58.694	30.244	47.056
	(4.290)	(6.898)	(11.005)	(4.149)	(4.394)
Tenure	12.357	11.768	10.792	11.157	9.899
	(0.587)	(1.272)	(1.153)	(0.634)	(0.363)
Establishment Size	62.207	48.000	95.426	110.137	191.818
	(16.134)	(13.419)	(21.399)	(23.820)	(64.362)
Prof., Man., Tech.	0.122	0.119	0.074	0.060	0.055
	(0.021)	(0.042)	(0.036)	(0.018)	(0.011)
Service	0.167	0.288	0.056	0.164	0.194
	(0.024)	(0.059)	(0.031)	(0.027)	(0.019)
Clerical and Sales	0.350	0.305	0.407	0.459	0.399
	(0.030)	(0.060)	(0.067)	(0.037)	(0.023)
Machine Work	0.114	0.169	0.093	0.109	0.157
	(0.020)	(0.049)	(0.040)	(0.023)	(0.017)
Bench Work	0.004	0.017	0.037	0.027	0.034
	(0.004)	(0.017)	(0.026)	(0.012)	(0.009)
Structural Work	0.093	0.085	0.130	0.060	0.073
	(0.019)	(0.037)	(0.046)	(0.018)	(0.012)
Starting Wage Obs.	243	58	53	182	435
Current Wage Obs.	240	57	54	180	433

Notes: Standard errors are in parentheses. The sample is limited to observations used in current or starting wage regressions. Relevant Experience and Tenure are measured in months.

Table 3. Starting Wage Regressions: Referral Types and the Effects of Initial Productivity

	I Pooled Regressions	II Wage Differences
Employee Referral	0.3338 (0.5373)	0.7876 (0.3245)
Employer's Frnd/Fam	0.6371 (0.7152)	0.0588 (0.3644)
Firm/Union Referral	-3.5395 (1.5538)	0.3859 (1.0538)
Other Referral	-0.2427 (0.5305)	0.3916 (0.3077)
Productivity	0.0073 (0.0074)	0.0096 (0.0039)
Prod. x Employee Ref.	-0.0005 (0.0110)	-0.0167 (0.0083)
Prod. x Employer Ref.	-0.0062 (0.0131)	-0.0017 (0.0075)
Prod. x Firm/Union Ref.	0.0721 (0.0392)	-0.0045 (0.0201)
Prod. x Other Ref.	0.0058 (0.0116)	-0.0075 (0.0071)
Observations	925	463 worker pairs

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

Table 4a. Current Wage Regressions: Referral Types, the Initial Effects of Productivity, and Employer Learning

	I Pooled Regressions	II Wage Differences
Employee Referral	-0.2947 (1.5209)	-1.6646 (0.7253)
Employer's Frnd/Fam	-2.8447 (1.3760)	2.6585 (0.9655)
Firm/Union Referral	-8.8154 (3.7595)	-1.5969 (1.3911)
Other Referral	-2.3894 (0.9091)	-0.1927 (0.8322)
Productivity	-0.0050 (0.0088)	0.0039 (0.0052)
Productivity x Tenure	0.0010 (0.0007)	0.0006 (0.0006)
Prod. x Employee Ref.	0.0124 (0.0180)	0.0196 (0.0101)
Prod. x Employer Ref.	0.0546 (0.0196)	-0.0278 (0.0120)
Prod. x Firm/Union Ref.	0.1013 (0.0435)	0.0266 (0.0155)
Prod. x Other Ref.	0.0336 (0.0103)	0.0021 (0.0113)
Prod x Tenure x Employee Ref.	-0.0017 (0.0014)	-0.0015 (0.0007)
Prod x Tenure x Employer Ref.	-0.0001 (0.0020)	0.0021 (0.0009)
Prod x Tenure x Firm/Union Ref.	-0.0130 (0.0046)	-0.0016 (0.0022)
Prod x Tenure x Other Ref.	-0.0017 (0.0008)	-0.0003 (0.0009)
Observations	893	447 worker pairs

Notes: Standard errors (in parentheses) are Huber/White allowing for dependence within survey site. The regression in column I includes a quartic polynomial in age; gender; dummy variables for education; relevant experience; tenure; missing-value dummies for age, education, experience, and tenure; and all appropriate interactions of tenure and its missing-value dummy variable. The job characteristics in column I are dummy variables for survey site, occupation and industry; number of employees in the establishment; the percent unionized and its missing-value dummy. The regression in column II controls for differences in individual characteristics used 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	0.3912 (0.2030)	-0.5561 (0.2404)	0.5314 (0.3103)	0.0413 (0.2268)
Tenure = 6 months	0.2064 (0.1463)	-0.3092 (0.1710)	0.3416 (0.0929)	0.0096 (0.1558)
Tenure = 12 months	0.0217 (0.1279)	-0.0624 (0.1470)	0.1518 (0.2520)	-0.0221 (0.1342)
Tenure = 18 months	-0.1630 (0.1614)	0.1845 (0.1869)	-0.0380 (0.5109)	-0.0539 (0.1807)

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

Table 4c. Current Wage Regressions: Effects of Referral Type on Wages at Average Performance.

	Employee	Employer's Friend or Family	Other Firm or Labor Union	Other Referral Sources
Tenure = 0 months	-0.1586 (0.1607)	0.5177 (0.1810)	0.4489 (0.3177)	-0.0335 (0.2897)
Tenure = 6 months	-0.1000 (0.1048)	0.3250 (0.1250)	0.4343 (0.2056)	-0.0708 (0.2026)
Tenure = 12 months	-0.0414 (0.0895)	0.1323 (0.1035)	0.4197 (0.2297)	-0.1081 (0.1483)
Tenure = 18 months	0.0172 (0.1299)	-0.0604 (0.1343)	0.4051 (0.3639)	-0.1454 (0.1638)

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. Average performance is rounded to 77.

Table 5. Effects of Referrals on Current Productivity

	I	II
Employee Referral	8.160	9.922
	(3.620)	(5.906)
Employer's Frnd/Fam	4.770	1.786
	(5.111)	(8.090)
Firm/Union Referral	14.842	22.192
	(6.943)	(8.041)
Other Referral	0.189	4.524
	(5.506)	(6.445)
Tenure	0.273	0.475
	(0.132)	(0.207)
Employee Referral x Tenure	…..	-0.195
		(0.423)
Employer's Frnd/Fam x Tenure	…..	0.168
		(0.446)
Firm/Union Referral x Tenure	…..	-0.790
		(0.316)
Other Referral x Tenure	…..	-0.380
		(0.473)
Observations	462 worker pairs	462 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; relevant experience; gender; dummy variables for education; missing-value dummies for experience, schooling, age and tenure; and the appropriate interactions of tenure's missing-value dummy.