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How Much Do Employers Learn from Referrals?

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(Preliminary)

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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 from the 1982 EOPP Survey of employers 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. My estimation results provide evidence consistent with referrals from friends and family members providing employers with more information than they would have otherwise. Despite the information they provide, however, it appears as though referrals from family members are associated with jobs that put less weight on performance overall. On the other hand, referrals from other employers or labor unions appear to provide little, if any, information but are associated with jobs that put more weight on performance than the average job does. I find no evidence that referrals from schools, community organizations or other sources provide useful information.

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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 an employer will have less to learn about a referred worker's productivity.

The importance of referrals to both the recruitment efforts of firms and the job search of individuals has long been known. Rees (1966) noted the importance of referrals as an informal recruitment method. More recently, Holzer (1987) found that referrals from employees and other employers produce new hires with higher performance and lower turnover. Holzer (1988), and Blau and Robbins (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 they would obtain through other hiring channels is not controversial. It provides and intuitively appealing explanation for the observations noted above and employers report that they find referrals to be informative. The observa-

tions in the previous literature related to referrals, however, would also arise if, for example, referred applicants were simply more capable workers on average. Furthermore, the surveys in which employers claim that referrals are informative (See Holzer (1987) for a review.) do little to confirm that the reports of employers are accurate. There is still a need, therefore, for work that examines whether or not employers actually behave in a way that suggests different types of referrals are informative.

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.

Unfortunately, there are a few problems that make it difficult to draw conclusions from Simon and Warner (1992). 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.[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 others.[2]

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

[2] Their relatively homogenous sample does not eliminate this problem, unless one believes

The tests the current paper presents 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 Jovanovic's matching framework. Aigner and Cain (1977), for example, 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 workers from groups that employers evaluate less accurately at the time of hiring. This paper performs the same tests, but considers the information employers obtain from different types of referrals compared to other recruiting methods.

The estimation in this paper uses data from the 1982 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 friends and family members providing employers with more information than they would have otherwise. Despite the information they provide, however, it appears as though referrals from family members are associated with jobs that

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.

put less weight on performance overall. On the other hand, referrals from other employers or labor unions provide little, if any, information but appear to be associated with jobs that put more weight on ability than other jobs do. Finally, 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 receive 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 sources 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 that received a referral of type j at the time of hiring:

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

where $\varepsilon_{sij} \sim N\left(0, \sigma^2_{\varepsilon j}\right)$ and $\sigma^2_{\varepsilon j}$ varies by referral type j. 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:

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

where β is common knowledge and σ^2_ν 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

$$E\left(\mu_{0i}|X_i, s_{ij}\right) = X_i\beta + \alpha_j\widetilde{s}_{ij} \tag{1}$$

where $\alpha_j = \frac{\sigma^2_v}{\sigma^2_{\varepsilon j}+\sigma^2_v}$. The more precise the signal is that results from a referral of type j, the smaller $\sigma^2_{\varepsilon j}$ is and the larger α_j is.

Of course, we might not observe s_{ij} in the data. What we do observe in the EOPP data is an employer-provided evaluation of the worker's performance at some tenure t, as well as a retrospective evaluation of initial performance taken at t. I assume the evaluation of performance at t is

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

where S_{tj} is an estimate of initial ability and $Z_t\gamma$ is the known effect of tenure and training on performance. 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 $\sigma^2_{\varepsilon j}$.[3] In other

[3] Pinkston (2003) derives S_{tj} using a standard Bayesian updating argument. As a result, S_{tj} is a weighted average of the employer's initial signal, s_{ij}, and a sequence of per period performance observations.

words, the precision of the performance 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 performance in the data is S_{tj}, we can write the estimated wage equation as

$$w_{0j} = X\beta + \alpha_j S_{tj} + \phi, \tag{2}$$

where $\phi = \alpha_j \left(\widetilde{s}_j - S_{tj}\right)$. The estimated coefficient $\widehat{\alpha}_j$ is obviously biased downward since ϕ is unobserved and correlated with S_{tj}. Pinkston (2003), however, shows that 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 will vary with tenure since S_{tj} will be less precise on average for a group that has lower average tenure.[4]

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

$$w_{tj} = E\left(\mu_t | X, P_t\right) = X\beta_{tj} + \alpha_{Pj} P_{tj}. \tag{3}$$

Pinkston (2003) shows that 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 important later learning is. Furthermore, at $t = 0$, α_{Pj} is an unbiased estimate of α_j from the starting wage equation.[5]

[4] This is assumming that the retrospective evaluation in the data is actually S_{tj}, not s_j (or s_j plus an error term). If the employer actually reports what he thought of the worker at the time of hiring, and not what he now thinks of the worker's initial ability as I have assumed, this is not a problem.

[5] This is assumming that employers learn about workers with the different types of referrals

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 cities. Each establishment is asked for information on the last worker hired, including evaluations of the worker's current performance and performance in the first two weeks on the job, as well as starting wage and current wage.

One of the key advantages of the EOPP data is that it contains a subsample of roughly 600 establishments that report data on two workers in the same job. I exploit this subsample by differencing the two workers in order to cancel out effects due to 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 they don't use the difference between the two workers; however, estimates that don't difference workers still use observations from workers who are paired with coworkers that are excluded due to missing values.[6]

The productivity evaluations in the data are the employer's ranking of the worker's productivity on that job on a scale of zero to 100. A rating of 100

a the same rate. If they learn more slowly about one group, estimates based on equation (2) would 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 recieve less reliable signals for one group than for another, we can be confident that our results are not due to this bias.

[6] 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.

indicates the maximum 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. I use the first and last of these evaluations and refer to them as "initial performance" and "current performance", respectively.

The data also contain questions about how the worker was hired; i.e., using a newspaper add, a referral from a friend, etc. This data allows me to separate workers who were hired using a referral from workers who were not, and even 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 a friend, workers referred by a family member, workers referred by another employer or a labor union, all other referrals and no referral at all.[7]

Finally, I set starting and current wages equal to missing if they are below $2 per hour, and drop observations in which age is reported to be less than 16. Since all observations are from the same survey year, I do not adjust for inflation. The resulting sample as roughly 550 worker pairs and 1150 individual workers.

[7] I group referrals from other employers and unions together due to sample size and because preliminary estimation suggests their effects are qualitatively similar. "Other" referrals come from schools, employment agencies, community organizations, etc.

Furthermore, referrals from friends and family members may combine referrals from friends or family members who work for the company with referrals from friends or family members of the employer. There are two questions on referral sources in the data, and the codebook that I have does not say which question refers to current employees and which refers to a friend or family member of the employer; however, Holzer (1987) separates referrals from current employees and referrals from friends or relatives of the employer. Making a guess based on numbers in Holzer (1987), roughly 20% of the referrals from friends in my data may be from friends of the employer while 10% of the referrals from family members are from the employer's family.

All tables that present estimates also present the number of observations used.

Table 1 presents summary statistics for my sample. The average starting wage is \$4.77 and the average current wage is \$5.55. The average worker's tenure is 10.4 months. The average initial performance of a worker, on a scale of 0 to 100, is 65.01, and the average current performance is 77.5. Finally, about 44% of the sample had no referral, 25% were referred by a friend, 8% by a family member, 5% by another employer or a labor union, and almost 18% were referred by some other source.

2.2 Estimation

In all of the estimation that follows, data from the different referral groups are pooled together. Regression estimates based on equation (2) take the form

$$w_{0j} = X\beta + \alpha S_{tj} + \sum_j \left(\gamma_j D_j + \alpha_j \cdot D_j \cdot S_{tj}\right) + \phi, \tag{4}$$

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 performance evaluation for those hired without referrals, and α_j captures the difference in the effect of performance 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:

$$w_{tj} = X\beta_{tj} + \alpha_0 P_{tj} + \alpha_t t P_{tj} + \sum_j \left(\gamma_j D_j + \alpha_{0j} \cdot D_j \cdot P_{tj} + \alpha_{tj} \cdot D_j \cdot t P_{tj}\right). \tag{5}$$

The coefficients on performance interacted with the group dummies 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. If the signals employers receive 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 performance and lower effect of learning for that group.

All regressions use wage levels, not logs.[8] The individual characteristics contained in X are age, age squared, experience the employer considers "relevant", hours of total training (the sum of formal and informal) in the first three months on the job, a dummy variable for there being no training, dummy variables for education level, and missing value dummy variables for age and experience. In some 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 valued dummy for that percent, and dummy variables for occupation, industry and survey site.

There are two related problems with estimates from equations (4) and (5). The first is that wages are likely influenced by firm- or job-specific factors which the job characteristics contained in the data can only proxy for. If the remaining job-specific components are correlated with performance or referral types, the results from equations (4) and (5) will be biased.[9] Secondly, the results could

[8] 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.

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

also be biased if workers in different referral groups tend to sort into jobs that differ in their sensitivity to individual performance. In that case, the wages of workers in jobs that were more sensitive to individual performance would put more weight on both initial performance and the information the employer learned about ability over time.[10]

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 (4) or (5) 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.[11] My preferred specifications, therefore, will exploit the differences between the two workers.[12]

3 Results

Table 2 presents results from starting wage regressions. The first two columns present regressions that pool all of the workers together instead of looking at

[10] 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.

[11] Roughly 65% 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. The only referral group that stands out in this respect is the group referred by a family member. Roughly 80% of workers with family referrals are paired with coworkers who did not receive a family referral.

[12] Another advantage to this approach is that it deals with the possibility that the performance evaluations are to some degree relative to the expectations of the specific job.

the difference between workers in the same job. The first column controls only for individual characteristics of the worker, while the second adds in the establishment and job characteristics discussed above. The third column then presents results from regressions that exploit the difference between workers in the same job. Estimates in the third column should not only be the least biased by any association between referral type and job type, but comparing them to the estimates in the first two columns should give some idea of how the relationship of referral type to job type biases the results.

The results in Table 2 suggest that referrals from friends who work for the company provide useful information that the employer would not have otherwise. Once job characteristics are differenced out in column 3, the coefficient on the performance evaluation interacted with a referral from a friend is 0.022 (0.005), while the coefficient on performance itself is much smaller and insignificant [0.005 (0.004)]. This implies that a difference of one standard deviation in the performance evaluation of a worker who was hired through a friend's referral will result in an hourly wage change of roughly $0.80, while the same difference in performance will only change the wage of a worker hired without a referral by a statistically insignificant $0.14.

None of the other coefficients on referral type interacted with the performance evaluation in the wage difference regression are statistically significant. At 0.0155 (0.010), the coefficient on the interaction of a referral from another employer or a union is the largest. In the second column, however, the analogous coefficient is 0.033 (0.017), which is significant. The fact that this coefficient

falls when job characteristics are more completely controlled for is consistent with workers who are hired using a referral from another employer or a labor union typically being in jobs that put more weight on individual performance, even though that type of referral may not be informative.

As is mentioned above, these starting wage results could be biased if the measure of initial performance, which is retrospective, measures 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,[13] I investigated this problem by estimating a simple wage difference regression that allowed the effect of the initial performance measures on initial wages to vary by tenure. The results provide no evidence that the effect of the initial performance measure on initial wages varies by tenure, which suggests it is unlikely that differences in tenure across groups would bias the starting wage results.

Even if there isn't bias due to the affect of tenure on the initial performance measure, there may still be problems with its use due to the fact that it is a retrospective measure. If the employer's recollection is not precise or is 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 average effect of performance on wages at the beginning of a job. Since both the wage and performance measures used in these regressions are either the current or most recent measures at

[13] Average tenure for those hired through the different referral types is as follows: friend's referral, 11.16 (0.482); family referral, 13.16 (1.088); employer/union referral, 10.34 (1.112); other referral, 10.5 (0.519); no referral, 9.44 (0.303). (Standard errors in parentheses.)

the time of interview, any bias in the results presented in Table 2 caused by the use of retrospective measures will be reduced in regressions of current wages on current performance.[14] Table 3 presents results from current wage regressions.

The results presented in Table 3 suggest that referrals from both friends and family members provide employers with useful information. Significantly more weight is put on performance initially for both groups. The interaction of a referral from a friend with performance has a coefficient of 0.0149 (0.0087) in column 3, while the coefficient on a family referral interacted with performance is even larger at 0.0389 (0.0107). Furthermore, employer learning has essentially no impact on the wages of either group. The coefficient on Performance $\times$ Tenure is 0.0011 (0.0005), while the coefficients on Performance $\times$ Tenure interacted with having a referral from a friend is -0.0012 (0.0007) and that on the interaction with a family referral is -0.0014 (0.0008). In more concrete terms, a one standard deviation increase in the performance measure at the beginning of a job will be associated with \$0.31 per hour more for a worker who was referred by a friend and \$0.80 per hour more for a worker who was referred by a family member; however, this advantage decreases over time as employers learn more about workers hired without a referral.

It's interesting to note that the coefficients on family interacted with performance and performance times tenure are small and insignificant in the regres-

[14] 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, making them less subject to retrospective errors than the initial measures would be. The only group that differs significantly from the others in the percent that are still employed by the firm are those with referrals from a friend, of whom 73% are still with the establishment.

sions that do not exploit differences between workers in the same jobs. This is consistent with referrals from family members being associated with jobs that put little weight on performance, even though the referrals are informative. This contrasts sharply with the evidence on referrals from other employers or unions, which is associated with much more weight being put on performance when not differencing workers, but a much smaller and insignificant amount of weight when workers are differenced. The coefficient on an employer or union referral interacted with performance is 0.1232 (0.0447) in Column 1 when no job characteristics are controlled for, but falls to 0.0178 (0.0135) when all job characteristics are differenced out. This is consistent with referrals from other employers or unions being associated with jobs that put a lot of weight on performance, even though they do not provide employers with useful information about job applicants.[15]

4 Discussion

The evidence presented by this paper suggests that referrals from an applicant's friends and family members provide employers with more information than they would have otherwise. Evaluations of the worker's performance have a larger (more positive) effect on wages at the time of hiring for these groups than for

[15] I also ran a regression that is analogous to the one presented in Column 1 of Table 3, but replaced the worker's own referral type with the referral type of the other worker in the same job. The information an employer has about a worker's performance 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 still be picked up. The results (not shown) again suggest that referrals from employers or unions are associated with more weight being put on performance. The coefficient on the other worker having an employer or union referral interacted with performance is 0.088 (0.046), but none of the other interactions are significant.

workers who where hired without a referral. Furthermore, there is significant evidence of employer learning for workers who are hired without a referral, but no such evidence for workers referred by a friend or family member. I do not find convincing evidence that referrals from other sources provide any useful information.

Because the data used in the paper provides information on two workers in the same job for a subset of firms, I am able to at least reduce any bias caused by different types of referrals being associated with different types of jobs while also getting some idea of how referrals are associated with job type. Despite the information they provide, for example, it appears as though referrals from family members are associated with jobs that put less weight on performance overall than other jobs do. On the other hand, referrals from other employers or labor unions provide little, if any, information but appear to be associated with jobs that put more weight on individual performance than other jobs do.

The finding that referrals from friends and family members provide employers with more information than other hiring channels do fits in nicely with other results in the literature. For example, Holzer (1988) and Blau and Robins (1990) find that these types of referrals are more effective than other search methods when it comes to producing offers and acceptances. Applying the statistical discrimination model developed in Cornell and Welch (1996) suggests that 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 family and friends have higher productivity, as reported by Holzer (1987); i.e., employers are likely to hire workers who are on average more productive the better able they are to distinguish which workers are more or less productive. Of course, workers who are hired through these referrals might also be more productive because they are drawn from a pool of applicants that is more productive on average, because the person who referred them is able to exert some 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	4.765	2.217	1156
Current Wage	5.546	2.679	1138
Initial Performance	65.010	29.990	1173
Current Performance	77.541	20.531	1173
Referred by Friend	0.246	0.431	1173
Referred by Family	0.082	0.274	1173
Referred by Emp/Union	0.051	0.220	1173
Other Referral Source	0.177	0.382	1173
No Referral	0.443	0.497	1173
High School	0.587	0.493	1173
Some College	0.187	0.390	1173
College	0.059	0.235	1173
Age	25.929	8.886	1143
"Relevant" Experience	43.816	57.650	615
Tenure	10.380	7.615	1111
Establishment Size	117.622	847.103	1173
Prof., Man., Tech.	0.086	0.281	1173
Service	0.189	0.392	1173
Clerical and Sales	0.382	0.486	1173
Machine Work	0.143	0.350	1173
Bench Work	0.026	0.158	1173
Structural Work	0.072	0.258	1173

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

Table 2. Starting Wage Regressions

	Pooled Regressions		Wage Differences
	1	2	3
Friend Referral	0.7528	0.8403	-0.6699
	(0.2926)	(0.3966)	(0.3064)
Family Referral	0.2638	0.4817	0.5655
	(0.6574)	(0.4213)	(0.3741)
Emp/Union Referral	-2.3935	-1.5440	-0.5047
	(1.5156)	(1.0404)	(0.6763)
Other Referral	-0.1792	-0.1499	0.1769
	(0.3592)	(0.4211)	(0.2757)
Performance	0.0069	0.0040	0.0045
	(0.0029)	(0.0027)	(0.0041)
Perf. x Friend Ref.	-0.0038	-0.0024	0.0218
	(0.0043)	(0.0031)	(0.0051)
Perf. x Family Ref.	-0.0017	-0.0060	-0.0031
	(0.0092)	(0.0043)	(0.0066)
Perf. x Emp/Union Ref.	0.0514	0.0331	0.0155
	(0.0328)	(0.0170)	(0.0100)
Perf. x Other Ref.	0.0025	0.0062	0.0057
	(0.0064)	(0.0064)	(0.0056)
Observable Job Characteristics	Not Included	Included	Differenced Out
Observations	1156	1156	546

Notes: Standard errors (in parentheses) are Huber/White allowing for dependence within survey site in columns 1 and 2. Regressions in columns 1 and 2 also include age, age squared, a dummy for age missing, dummy variables for gender and education, "relevant" experience and its missing value dummy, total hours of training and a dummy variable for zero training. The job characteristics in column 2 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 dummy variable for the percent unionized. Regressions in column 3 are estimated in SAS using Proc Model, and control for differences in age, it's missing value dummy, gender, relevant experience, its missing value dummy, training, the dummy for zero training, and a dummy variable for each worker equal to one if that worker attained a higher level of education that than other.

Table 3. Current Wage Regressions

	Pooled Regressions		Wage Differences
	1	2	3
Friend Referral	-1.7488	-0.8250	-1.0008
	(1.3315)	(1.0096)	(0.6537)
Family Referral	1.4247	1.3082	-4.1433
	(1.4346)	(1.5298)	(0.7994)
Emp/Union Referral	-9.4308	-5.5331	-0.9336
	(3.0913)	(1.8474)	(1.0758)
Other Referral	0.0027	-1.1697	0.1269
	(0.9635)	(1.0247)	(0.6868)
Performance	0.0020	-0.0047	0.0045
	(0.0107)	(0.0091)	(0.0053)
Performance x Tenure	0.0005	0.0009	0.0011
	(0.0009)	(0.0007)	(0.0005)
Perf. x Friend Ref.	0.0358	0.0266	0.0149
	(0.0154)	(0.0144)	(0.0087)
Perf. x Family Ref.	-0.0114	-0.0141	0.0389
	(0.0145)	(0.0186)	(0.0107)
Perf. x Emp/Union Ref.	0.1232	0.0714	0.0178
	(0.0447)	(0.0257)	(0.0135)
Perf. x Other Ref.	-0.0013	0.0166	0.0000
	(0.0138)	(0.0151)	(0.0091)
Perf x Ten x Friend Ref	-0.0021	-0.0019	-0.0012
	(0.0011)	(0.0012)	(0.0007)
Perf x Ten x Family Ref	0.0005	0.0001	-0.0014
	(0.0013)	(0.0013)	(0.0008)
Perf x Ten x Emp Ref	-0.0043	-0.0030	-0.0015
	(0.0040)	(0.0021)	(0.0014)
Perf. x Ten x Other Ref.	-0.0003	-0.0013	-0.0003
	(0.0020)	(0.0017)	(0.0008)
Observable Job Characteristics	Not Included	Included	Differenced Out
Observations	1138	1138	523

Notes: Standard errors (in parentheses) are Huber/White allowing for dependence within survey site in columns 1 and 2.
Regressions in columns 1 and 2 also include age, age squared, a dummy for age missing, dummy variables for gender and education, "relevant" experience and its missing value dummy, total hours of training, a dummy variable for zero training, tenure, a missing value dummy for tenure, and all appropriate interactions of that missing value dummy.
The job characteristics in column 2 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 dummy variable for the percent unionized.
Regressions in column 3 are estimated in SAS using Proc Model; and control for differences in age, it's missing value dummy, gender, relevant experience, its missing value dummy, training, the dummy for zero training, a dummy variable for each worker equal to one if that worker attained a higher level of education that than other, differences in tenure, it's missing value dummy, and the appropriate interactions of that missing value dummy.