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Peter F. Kostiuk and others .
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2.   This is one of several publications prepared in connection with CNA's Selected Reserve Utilization of Personnel Resources Study. This Research Contribution examines the importance of experience on recruiting duty on the productivity of Naval Reserve recruiters. It contains additional documentation and technical details of the analysis previously published in reference (a).

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Learning Curves, Personal Characteristics, and Job Performance

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Dean A. Follmann
James F. Grogan

Navy-Marine Corps Planning and Manpower Division

ABSTRACT

This research contribution uses data on the productivity of Naval Reserve recruiters to estimate the effects of on-the-job learning, experience, and individual characteristics on job performance. The econometric approach begins with the Poisson distribution whose mean is assumed to be a function of explanatory variables. Generalizations are specified to control for individual heterogeneity as well as over-dispersion.

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INTRODUCTION

Empirical studies of earnings and productivity have found education and experience, both general and with a particular employer, to be important determinants.[1] Human capital theory provides one explanation for the observed positive relationship among experience, education, and earnings, and in recent years the theories of screening [5] and incentive problems [6] have supplied competing hypotheses. According to human capital theory, education and experience are productivity-enhancing, and therefore workers with more education or greater experience earn higher incomes. In the screening and incentive explanations, there does not necessarily have to be a contemporaneous correlation between productivity and income, and the role of education and experience in determining productivity is ambiguous.

Distinguishing among these competing explanations of earnings functions is generally not feasible with data on earnings alone, since these explanations hinge crucially on the effects of personal characteristics on productivity. Unfortunately, productivity data on individuals are rarely available, and when they are, the data are usually subjective evaluations such as supervisory ratings, or the productivity measures are incomplete indexes of the true scope of the job. Consequently, few studies have been made of productivity at the individual level. References [7] and [8] use supervisory ratings to examine the effects of experience, and there have been several studies of the productivity of military personnel [9, 10, 11]. References [7] and [8] find that experience has little effect on ratings, although the usefulness of ratings as an accurate index of productivity is questionable. Reference [12] estimates strong experience effects during the first four years of Navy enlistments and also finds a positive impact of education. Reference [10] indicates a significant productivity difference between high school graduates and non-graduates during the first term of enlistment, but little effect thereafter.

To determine how the effects of on-the-job learning, experience, and individual characteristics affect job performance, the analysis uses data on the productivity of Naval Reserve recruiters. Productivity is measured as the number of enlistment contracts signed in a month. The sample of recruiters provides a comprehensive and *objective* measure of job performance, which makes it possible to study the effects of numerous factors on individual productivity. The variables analyzed include individual traits, such as education and experience, and factors affecting the supply of enlistments, such as the unemployment rate. Given the small integer character of the productivity measure, the analysis begins with a Poisson distribution to describe the process. Extensions to different generalizations of the Poisson model are then estimated to examine the sensitivity of the results and to compensate for obvious inadequacies with the Poisson model. The results of the study provide insights into the effects of demographic characteristics on productivity and the impact of experience. In particular, the findings indicate that learning on the job is an important determinant of productivity.

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1. References [1] and [2] provide theoretical and empirical analyses of the effects of education and experience. More recent evidence on the effect of job tenure can be found in [3] and [4].

BACKGROUND

Naval Reserve recruiters are full-time naval personnel with the job of recruiting enlistments into the Naval Reserve. Most recruiters are reservists who volunteered to go on active duty and were given one-year renewable contracts to serve as recruiters. For those on one-year contracts, poor performance may result in dismissal before the contract expires, and the individual would then revert to civilian status.

The sources of enlistments are military veterans who have completed active-duty tours and non-prior-service (NPS) individuals. NPS enlistments come in two types: those with specific skills valued by the Navy (such as carpenters or nurses) who receive advances in pay grade when they enlist, and others without technical skills who are trained by the Navy.

Individuals enlisting in the Naval Reserve incur a contractual obligation for a specified period of time (usually about three years). The reservist's responsibilities are to attend drills one weekend a month and go on active duty for two weeks a year. For individuals with critical skills, there are financial incentives to enlist and remain in the reserves.

There are several entry programs into the Naval Reserve, determined largely by whether the individual has previously served on active duty, the type of duty, and military service. In this analysis, all recruits are classified into two categories. The first group, referred to as Selected Reservists (SELRES), includes Navy veterans, Active Mariners, other service veterans, and advanced pay-grade personnel.[1] The second category comprises individuals enlisting in the SAM program. SAM recruits are analyzed separately because they have no prior military training or critical skills and a more stringent contractual obligation. Under some circumstances, SAMs who stop attending drills may be ordered to active duty. For this reason, and because SAMs come from a different recruiting market (primarily high school seniors) and may be more difficult to recruit, they are counted separately.

Unlike most occupations, recruiting has a well-defined measure of individual productivity—the number of enlistments brought in. Although there are some complications due to the two categories of personnel recruited, it is not as difficult to adjust for recruit quality when calculating Naval Reserve recruiting productivity as when calculating the productivity of active-duty recruiting. The primary source of reserve recruits are those sailors who have already demonstrated their ability to successfully deal with Navy life and are aware of the benefits and responsibilities that go along with it. Moreover, the reward system in place for recruiters specifically identifies enlistments as the primary factor determining a recruiter's success or failure. Although recruiting performance is also measured by the number of points earned (different recruit categories are worth varying amounts of points) as well as total enlistments, the analysis considers contract totals to be the measure of productivity. Points do play a role in personnel evaluation, primarily for determining commendation awards. Nevertheless, for the past several years the Naval Reserve has emphasized the need to increase the size of the force, and thus emphasis was placed on maximizing enlistments.

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1. The term SELRES is used to be consistent with the definitions used by Commander, Naval Reserve Force (COMNAVRESFOR) in its recruiting reports. The term is not meant to imply that SAMs are not members of the Selected Reserve.

DATA DESCRIPTION

The recruiting data used in the analysis were obtained from the Recruiting EDP Standard User Logistics Tracking System (RESULTS) module of the Reserve Training and Support System (RTSS) maintained by the Commander, Naval Reserve Force (COMNAVRESFOR). Data records in the original files contain information on each recruit brought into the Naval Reserve from October 1982 through September 1986. Although it is primarily a recruit file, RESULTS also identifies by social security number (SSN) the recruiter who received credit for the enlistment. The productivity file was constructed by aggregating over recruiter SSN and enlistment date for each enlistment category. Because RESULTS contains incomplete data on SAM recruiting, such information was obtained from a separate file that tracks SAM recruiting and accessions. This information was then merged into the RESULTS system.

Two sources provided data on the individual characteristics of the recruiters. The recruiter billet file, which is part of the RESULTS system, provided data on current recruiters, including age, sex, race, and pay entry base date. Because that file only has data on current or recently departed recruiters, supplemental information was obtained from the Enlisted Master Record (EMR), which also provided information on the recruiter's education. If a recruiter was not on either file, or if some of the key data elements were missing, the individual was dropped from the sample.

Months of experience in recruiting were calculated from the month in which the recruiter first appears in the file. Because a record exists only if the recruiter made an enlistment during that month, it is possible that experience will be slightly underestimated if recruiters spend a few months on duty before recording their first enlistment. After the recruiter first appears in the file, it is possible that some months will be missing because he did not recruit anyone, even though he was actively trying. Since these factors will bias the estimates of the effects of experience, new records were added to the file if it was determined that the recruiter was working but did not have any success in a particular month. These determinations were made by tracking the recruiter's career and inserting zero enlistment records when gaps of three months or fewer occurred. Although this may cause additional problems if the recruiter was not actually on duty (perhaps on sick leave or attending a training program), it was decided that this solution was preferable to ignoring the bias due to missing observations. The vast majority of imputed zero-contract months occur during the first year of recruiting duty, when it would be expected that recruiters would be more likely to have bad months and at the same time not be taken off recruiting duty for other tasks.

For recruiters on duty in October 1982, the first month in the sample, the method for calculating experience is not applicable. The analysis attempted to use the date on which the recruiter first went on recruiting duty (a variable in the recruiter billet file), but the results were unreliable because in many cases a recruiter's start date from the billet file is after the time when the recruiter was first observed recruiting from the RESULTS data. Therefore, those recruiters who began before October 1982 were dropped from the sample.

Local recruiting market conditions were merged in by state. The recruiter's location was determined by the location of the unit that received credit for the enlistment. When the recruiter operated in more than one state, data from the state with the most enlistments ·

were used. The state-level data used in the analysis are monthly unemployment rates and the number of Navy veterans who left active duty in the previous 12 months and listed that state as their home of record.

These data are complicated because recruiters switch from recruiting one type of enlistment to another. At the beginning of the sample period recruiters only enlisted SELRES personnel. In September 1983, the SAM program was instituted and some recruiters started to recruit for this new category. Because the market and the perceived value by the Navy of SAMs and other personnel differs, measuring productivity by the number of enlistments is not comparable for recruiters who recruit the two types. This paper focuses on SELRES recruits with some allowance for a division of effort for those recruiters who signed up both SAM and SELRES recruits. The dependent variable in all cases is the number of SELRES enlistments. When both SAM and SELRES contracts were sought by the same recruiter in the same month, the number of SAM enlistments was included as an explanatory variable, thereby generating an estimate of the trade-off involved in recruiting the two personnel categories.

Sample means for the data are provided in table 1. Each observation is a recruiter-month in which the recruiter was actively recruiting SELRES enlistments. There are 775 recruiters, with a total of 9,730 observations. The average number of enlistments was 3.6 per month, plus 0.5 SAM. Most of the recruiters were relatively inexperienced, and the average time spent on recruiting was 11 months. Most recruiters have high school educations; less than 5 percent are non-high school graduates and only around 4 percent have a college degree. In addition, most recruiters have spent a long time in the Navy, with an average length of service (LOS) of 12 years and mean pay grade of nearly E-6.

Table 1. Sample means

Variable	Mean	Standard deviation	Minimum	Maximum
SELRES enlistments	3.64	2.61	0	21
Recruiting experience (months)	10.9	8.8	1	47
Percent NHSG	0.042			
Percent with BA	0.037			
Percent women	0.126			
Percent nonwhite	0.065			
Percent married	0.834			
Length of military service (years)	11.8	5.4	0	38
Pay grade	5.7	0.9	2	9
Log population	7.76	0.9	4.4	9.0
Unemployment rate	7.5	2.1	0.5	20.6
SAM contracts	0.51	1.0	0	11
Number of observations	9,730			
Number of recruiters	775			

NOTE: The population for the SELRES sample is the number of Navy veterans who left active duty in the last 12 months, allocated to states by their home of record.

Figure 1 provides the average number of recruits signed up by months of recruiter experience. There is an increase in productivity until about one year, after which productivity levels off. The average number of recruits from recruiters with three and a half years of experience or more widely fluctuates, reflecting the relatively few number of recruiters with this much experience.
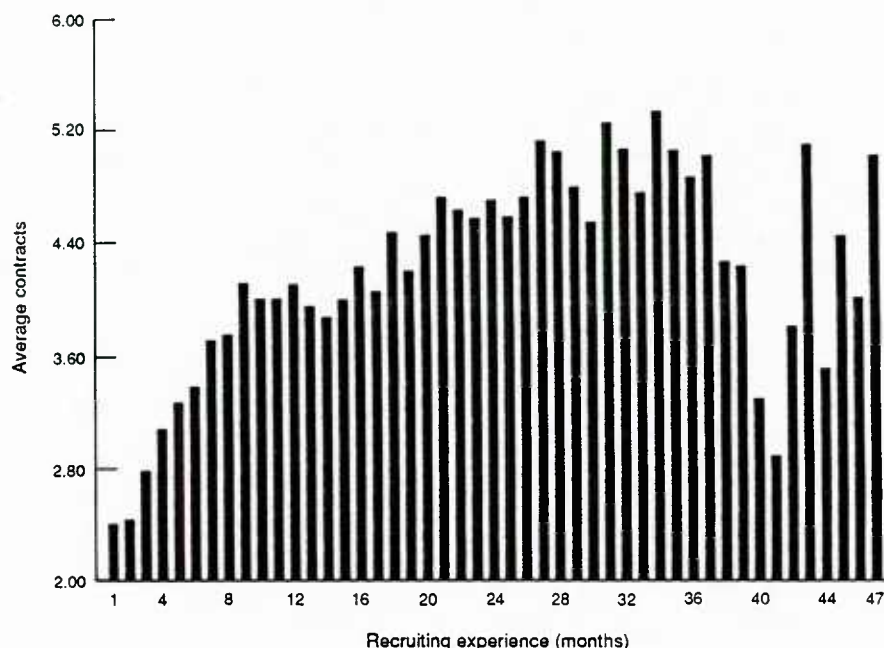

Figure 1. Average contracts per month

The richness of the data allows examination of two aspects of the effect of experience. Most studies are restricted to measuring time with an employer, without information on job changes within the firm. If different jobs within the organization require learning time, total tenure may be a poor predictor of productivity. In this sample, all of the recruiters have been with the same organization for a long time, but vary in the amount of time they have spent as recruiters. Time spent on recruiting duty—the experience variable—allows estimation of a learning curve for a particular occupation. General experience, or tenure, which in this sample means length of military service, can also be controlled. Greater detail is available by including the military grade level, which further differentiates among individuals with the same levels of experience.

Statistical Model

Productivity is measured by the number of recruits a recruiter signs up in a month (N). The appropriate statistical model is required to answer questions about the effect of education and experience on productivity. Linear models based on the normal distribution are suspect since the measure of a recruiter's productivity is a small integer and frequently zero. A Poisson distribution, which is defined on the integers, provides a

better initial model. Potential problems with some of the requirements of the Poisson model, however, suggest that alternatives may be required. Some of these options are explored in the next section.

The Poisson model is given by

$$Pr(n_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{n_{it}}}{n_{it}!} \quad , \tag{1}$$

where n_{it} is the number of enlistments for recruiter i in month t and λ_{it} is the Poisson parameter. For the Poisson distribution, λ_{it} also is the mean or expected number of enlistments as well as the variance. To allow for the effects of exogenous variables, λ_{it} is set equal to $e^{X_{it}\beta}$, where X_{it} is a vector of explanatory variables and β is the coefficient vector. In this specification, each observation has a different mean $(= \lambda_{it})$ and n_{it} is random because of the probabilistic nature of the Poisson distribution.

Assuming that the observations are independent (an assumption that will be relaxed in later sections), the log-likelihood function for the basic Poisson model is

$$\ell(\beta) = \sum_{i=1}^{N} \sum_{t=1}^{T_i} n_{it} X_{it} \beta - e^{X_{it}\beta} - log \; n_{it}! \; , \tag{2}$$

where N is the number of recruiters and T_i is the number of observations for the *ith* recruiter.

Parameter estimates are calculated by maximizing the log-likelihood function by a numerical optimization program. Two estimates of the Hessian matrix are used to obtain estimates of the asymptotic standard errors. The first method computes the covariance matrix as the inverse of the second derivative of the likelihood function:

$$\sum_{H} = -\left[\partial^2 \ell(\beta)/(\partial\beta_j)(\partial\beta_k)\right]^{-1} \; . \tag{3}$$

The second estimate, referred to as the Gradient estimate, uses the inverse of the product of the gradient of the likelihood function:

$$\sum_{G} = \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[\partial\ell_{it}(\beta)/\partial\beta_j\right] \times \left[\partial\ell_{it}(\beta)/\partial\beta_k\right] \right\}^{-1} \; . \tag{4}$$

The square roots of the diagonal elements provide the standard errors of the parameter estimates.

Explanatory variables were obtained from table 1. Figure 1 indicates a non-linear effect of experience on recruiter productivity and a third-degree polynomial for experience was specified. This polynomial allows for a shape similar to that of figure 1.

Table 2 provides estimates of this model. Several interesting findings are immediately apparent. There is a sharp experience profile that does not level off until around 22 months and remains flat until the extreme of the sample (47 months) is reached. The estimates indicate that expected output is twice as high at 22 months as it is in the recruiter's first month. Most of the productivity growth occurs in the first year, but there is still a 12-percent increase in the second year.

Table 2. Poisson regression estimates for SELRES contract—standard model

	Parameter estimate	Asymptotic standard error	
		Hessian	Gradient
Intercept	0.3291	0.0688	0.0510
NHSG	0.0351	0.0261	0.0183
BA	−0.0445	0.0290	0.0221
LOS	−0.0064	0.0012	0.0009
EXP	0.0796	0.0041	0.0033
EXP2/100	−0.2838	0.0249	0.0206
EXP3/10,000	0.3156	0.0413	0.0351
Woman	0.0669	0.0174	0.0129
Nonwhite	−0.0514	0.0227	0.0170
Married	0.1132	0.0160	0.0121
Pay grade	0.0521	0.0076	0.0057
Population	0.0370	0.0059	0.0042
URATE	−0.0110	0.0027	0.0022
SAMs	−0.0804	0.0061	0.0042

Log likelihood = −22,579

NOTE: There are 9,730 observations.

Recruiters with higher pay grades are more productive, as expected. Once pay grade is controlled for, however, the effect of LOS is negative, although not very large. One possible explanation for this negative result is that LOS is associated with unobserved ability differences; that is, individuals with high LOS but low pay grades are less able, which is why they were not promoted as rapidly. A potentially serious problem may be that there is no adjustment for part-time versus full-time military service. If, for example, a recruiter had been a part-time reservist for four years after

getting off active duty, his calculated LOS would be the same as the calculated LOS for someone who had been full time during that period.

The recruiting market variables—population and unemployment rate—perform poorly, with the unemployment-rate estimate having a counter-intuitive sign. This is not too surprising because the model does not control for location effects, which previous research has shown to be important. Among the personal characteristics, women are slightly more productive and married recruiters are significantly more productive. Most studies of wage determination contain similar results on marital status.

The estimated effect of education, or lack of one, is particularly intriguing. Most studies of earnings estimate a significant positive coefficient on years of education, or as specified in this report, on educational levels [1, 2]. Even within the Navy, some studies [12, 13] have shown education to have positive effects on productivity. The absence of such an effect, or even a negative impact, in this data set is most likely due to selection biases. Most of the recruiters in the sample are career Navy personnel who have been in the service for at least several years and are in relatively high pay grades. To remain in the Navy and get promoted, these individuals must have demonstrated some level of competence. Therefore, individuals who make it into the sample have already been through a selection process several times and have demonstrated above-average ability for their cohort. This is a typical case of selection bias in which the lower tail of the distribution has been truncated. In particular, those non-high school graduates (NHSG) who successfully met all previous hurdles and made it into the sample are going to be well above the average for their educational level. Although it is possible that there is selection bias operating in the assignment process as well (that is, systematic assignment of good or bad personnel to recruiting duty),[1] this is likely to be much less important than the survival process that filters out less able personnel before they have acquired the necessary seniority to become recruiters. The results of this analysis are consistent with those found in [10], in which there was a negligible effect of education on senior enlisted personnel (pay grades E-5 and above), but about a 15 to 20 percent greater productivity for HSG versus NHSG in the lower pay grades.

When viewed in a similar censoring framework, the negative although statistically insignificant effect for college graduates is not so surprising. College graduates are rare in the enlisted Navy (they make up only 3.7 percent of the observations in the sample) and those that make the enlisted Navy a career are likely to be below average for their educational level. (More able college graduates who start as enlisted personnel are sometimes offered the opportunity to become commissioned officers.)

The assumptions of the standard Poisson model are somewhat restrictive and require further investigation. Particularly questionable is the assumption that the mean and the variance are equal. This is examined by calculating the standardized residual

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1. Since recruiting duty is voluntary, this is not likely to be an assignment problem. Nevertheless, most recruiters hired in the past few years left civilian jobs to return to the Navy. The most common reasons for doing this are related to personal traumas (e.g., loss of job, marital dissolution); thus, the sample is obviously not typical.

$r_{it} = \left(n_{it} - \hat{\lambda}_{it}\right)/\sqrt{\hat{\lambda}_{it}}$. If the assumption of equal mean and variance of the Poisson model is true, r_{it} should have a variance of 1. Instead, the estimated standardized residual variance is 1.70, indicating that the amount of dispersion in the data is greater than assumed. An alternate test [14] is to compare the estimated means and variances for each recruiter and determine whether they have the assumed one-to-one relationship. A regression of $log\ \sigma_i^2$ on $log\ \bar{\lambda}_i$ yields a coefficient of 1.88, again demonstrating that there is over-dispersion in the data.

The likelihood function was based on the assumption of independent observations, which ignores the possibility of individual recruiter effects. Testing this assumption with the estimated residual covariance matrix (as in [14]) is not feasible with the unbalanced data used in this sample. As a descriptive substitute, the first-order autocorrelation among the residuals was estimated and found to be 0.11, which indicates that the independence assumption may be invalid.

Further evidence of misspecification of the Poisson model is obtained from comparing the two estimates of the standard errors of the coefficients. The estimates differ quite a bit, often by about 50 percent. The two estimates have the same expected value if the specification is correct (as in [15]), which also indicates that the standard Poisson model may be inadequate. Finally, a Pearson chi-square statistic

$$X^2 = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \frac{\left[n_{it} - \hat{\lambda}_{it}\right]^2}{\hat{\lambda}_{it}} \tag{5}$$

has a value of 16,589 on 9,715 degrees of freedom.[1] This is highly significant, indicating that the Poisson model is inadequate. Because the $n_{it}s$ are generally small, however, this result should be interpreted cautiously.

Alternative Specifications

The preceding analysis shows that the basic Poisson model is insufficient because it does not incorporate over-dispersion and correlation among individual recruiter observations. In this section, the basic model is expanded to overcome these deficiencies. The first model extends the basic model by incorporating random individual effects. The derived model is in the class of mixture models that were analyzed in the reliability literature [17], in an economic setting in [14] and [18], and in an epidemiological context in [19] and [20].

Each recruiter is assumed to receive a random draw from a distribution that affects average productivity proportionally in all observations. Let $\lambda_{it}^* = \alpha_i \lambda_{it}$ be the Poisson parameter, with λ_{it} defined as before and α_i the random recruiter effect. The parameter α_i comes from a random distribution, but for each recruiter, α_i is a fixed value. The random α_i creates a correlation between observations for that recruiter, but not among

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1. Assuming the model is true, the asymptotic (as the n_{it} increase) distribution of X^2 is chi-square with degrees of freedom given by the number of Poisson counts minus the number of parameters (refer, for example, to [16]).

different recruiters. Therefore, the random-effects model incorporates autocorrelation between observations, and it can also be shown that the variance increases with λ^*, which adds some desirable over-dispersion.

Incorporating explanatory variables as before, the random-effects specification becomes $\lambda_{it}^* = \alpha_i e^{X_{it}\beta}$, and X contains an intercept. The probability that recruiter i in period t recruits n_{it} enlistments is

$$Pr\left(n_{it} \mid X_{it}, \, \alpha_i\right) = e^{-\alpha_i \lambda_{it}} \frac{\left(\alpha_i \lambda_{it}\right)^{n_{it}}}{n_{it}!} . \tag{6}$$

If α_i is assumed to be uncorrelated with X_{it}, the joint probability density of the observations for a recruiter i and the random effect α_i becomes

$$Pr\left(n_{i1}, \ldots, n_{iT_i}, \alpha_i\right) = e^{-\alpha_i \Sigma_t \lambda_{it}} \, \alpha_i^{\Sigma_t n_{it}} \, \Pi_t \frac{\lambda_{it}^{n_{it}}}{n_{it}!} \, g(\alpha_i) , \tag{7}$$

where $g(\alpha_i)$ is the density of α_i. By assuming a specific probability distribution for the random effect α_i, the random effects can be integrated out from the equation. A common assumption, which is used in this report, is to assume that α_i is distributed as a gamma random variable with parameters (δ, δ), so that the mean is 1 and the variance is $1/\delta$. The mean is taken to be unity because X has an intercept term. Upon integrating, an individual recruiter's likelihood function is produced:

$$L_i(\beta, \delta) = \left[\frac{\delta}{\delta + \Sigma_t \lambda_{it}}\right]^{\delta} \left(\Sigma_t \lambda_{it} + \delta\right)^{-\Sigma_t n_{it}} \frac{\Gamma(\delta + \Sigma_t n_{it})}{\Gamma(\delta)} \Pi_t \frac{\lambda_{it}^{n_{it}}}{n_{it}!} , \tag{8}$$

where $\Gamma(z)$ is the gamma function. The likelihood function for the entire sample is simply the product of the individual recruiter likelihood functions.

This model specification has $E\left[N_{it}\right] = \lambda_{it}$, $V\left[N_{it}\right] = \lambda_{it}\left(1 + \lambda_{it}/\delta\right)$ and $COV\left[N_{it}, N_{is}\right] = \lambda_{it}\lambda_{is}/\delta$. The variance to mean ratio is $1 + \lambda/\delta$, which increases with λ. Therefore, the random-effects specification allows for both over-dispersion and individual recruiter effects through the α_i. Also, it allows for a positive correlation among the number of recruits for different months for the same recruiter. The principal drawback of the model is the assumption that individual effects are uncorrelated with X, an assumption that is usually violated in individual data of this sort. A model that relaxes this assumption will be presented in the next section.

Table 3 presents the estimates based on the random-effects Poisson model for SELRES contracts. Standard errors were estimated using the Gradient method and the expected value of the Hessian matrix. The addition of population heterogeneity improves the fit of the model considerably, as indicated by the larger log-likelihood value of $-21,170$ as compared to $-22,579$ for the basic Poisson. Many of the coefficients are different, especially the two education-level variables. There is now no difference in

productivity between non-graduates and graduates, but those with college degrees fare much worse than before, with a 10-percent shortfall. The experience profile is slightly flatter, and sex has a smaller impact and race a larger one. The estimated population heterogeneity variance is $1/\delta$, or 0.17. This demonstrates a large degree of variation in individual productivity: plus or minus twice the standard deviation of α from its mean (unity) gives a range of (0.18, 1.82). The results clearly demonstrate the need to control for heterogeneity when analyzing productivity.

Table 3. Random-effects Poisson estimates for SELRES enlistments

	Parameter estimate	Asymptotic standard errors	
		Hessian	Gradient
Intercept	0.1599	0.1562	0.1882
NHSG	0.0008	0.0924	0.0903
BA	−0.1072	0.0864	0.0928
LOS	−0.0071	0.0036	0.0039
EXP	0.0658	0.0028	0.0046
EXP2/100	−0.2515	0.0165	0.0276
EXP3/10,000	0.2996	0.0280	0.0458
Woman	0.0315	0.0525	0.0538
Nonwhite	−0.0810	0.0667	0.0707
Married	0.0879	0.0491	0.0486
Pay grade	0.0461	0.0241	0.0242
Population	0.0560	0.0111	0.0164
URATE	0.0039	0.0037	0.0051
SAMs	−0.0703	0.0044	0.0071
Delta	5.6416	0.3730	0.4266

Log likelihood = −21,170.439

NOTE: There are 9,730 observations.

As an indication of the model fit, the standardized residual $r_{it} = \left(n_{it} - \hat{E}[N_{it}]\right) \sqrt{\hat{V}[N_{it}]}$ was calculated. The mean-squared residual was 1.18, compared to the mean-squared residual of 1.70 for the basic Poisson model, which indicates a substantial improvement in model fit. The mean residual is still much larger than the expected value of 1; thus, the correction for over-dispersion is incomplete.

A possible drawback of the random-effects specification is the assumption of no correlation between the unobserved random effects and the explanatory variables. This assumption made it possible to integrate out the individual effects and thereby get a tractable likelihood function. In many instances, however, it is invalid to assume that the unobserved effects are uncorrelated with individual characteristics [21]. To examine this

assumption, recruiter residuals $r_i = \left(\Sigma_t n_{it} - \hat{E}\left[\Sigma_t N_{it} \right] \right) / \sqrt{\hat{V}\left[\Sigma_t N_{it} \right]}$ were calculated and their variation with the X variables examined. There appeared to be little correlation among all variables except experience. Figure 2 presents the recruiter residuals plotted against a recruiter's experience. The correlation of 0.22 underscores the relationship between the two. Additionally, even if there is no correlation, the assumption of a gamma distribution for the recruiter effects, although mathematically convenient, may be unwarranted.
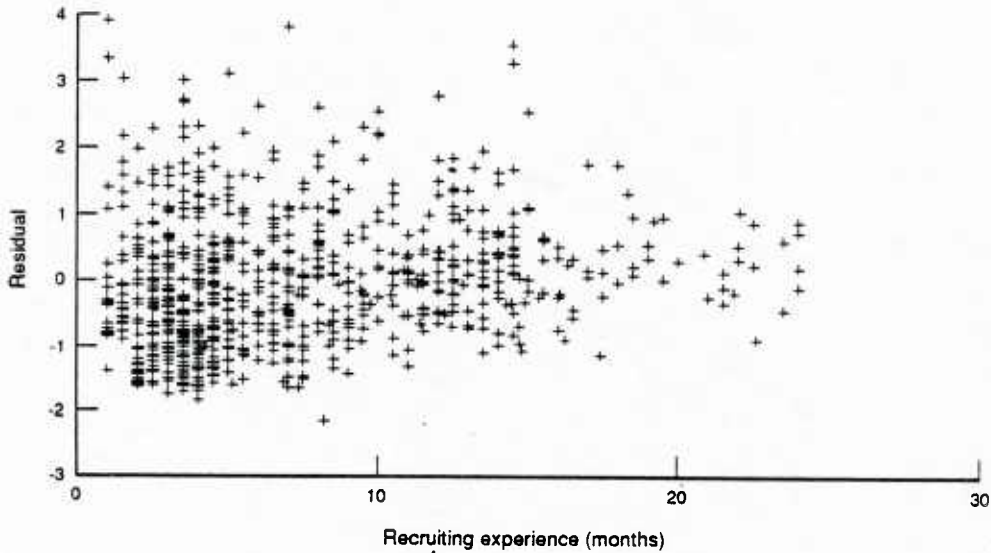

Figure 2. Random-effects model residuals by experience

A fixed-effects model, which is a generalization of the random-effects model, may overcome some of the above problems. Under a fixed-effects model, a dummy variable for each recruiter is inserted into X. This should reduce the amount of over-dispersion as well as deal with the correlation between the recruiter effects and experience. Additionally, specification of a particular mixing distribution is avoided. Reference [18] cautions against choosing a mathematically convenient distribution. Although including 775 recruiter effects greatly increases the number of parameters, it can be shown (e.g., in [22]) that the fixed-effects model decomposes into two parts: a Poisson model for $\Sigma_i N_{it}$ and a multinomial model for the $N_{it}s$ given $\Sigma_t N_{it}$. The Poisson model contains the recruiter parameters and the multinomial model involves only the coefficients of X variables that change over time. If interest centers on just these coefficients, only the multinomial model needs to be estimated. Thus, the asymptotic problems associated with an increasing number of parameters are avoided.

The result that the multinomial model is adequate for inference about β can also be derived directly. The direct derivation is based on the conditionality principle (e.g., in [23]), which states that if some parameters are regarded as *nuisance* parameters and sufficient statistics for these nuisance parameters exist, the analysis should condition on

these sufficient statistics for inference about the parameters of interest. To apply this principle to the recruiter sample, first note that $\Sigma_t n_{it}$ is a sufficient statistic for $\Sigma_t \lambda_{it}^*$, where λ_{it}^* is defined as before $(= \alpha_i \lambda_{it})$. By conditioning on $\Sigma_t n_{it}$ and using the fact that $\Sigma_t n_{it}$ is distributed as a Poisson random variable with parameter $\Sigma_t \lambda_{it}^*$, the multinomial distribution results:

$$Pr\left(n_{i1}, n_{i2}, \ldots, n_{iT_i} \Big| \sum_{t=1}^{T_i} n_{it}\right) = \frac{Pr\left(n_{i1}, n_{i2}, \ldots n_{iT_i}\right)}{Pr\left(\Sigma_{t=1}^{T_i} n_{it}\right)} \tag{9}$$

$$\left[\frac{e^{-\Sigma_{t=1}^{T_i} \lambda_{it}^*} \Pi_t \left(\lambda_{it}^*\right)^{n_{it}}}{\Pi_t n_{it}!}\right] \left[\frac{e^{-\Sigma_{t=1}^{T_i} \lambda_{it}^*} \left(\Sigma_{t=1}^{T_i} \lambda_{it}^*\right)^{\Sigma_{t=1}^{T_i} n_{it}}}{\left(\Sigma_{t=1}^{T_i} n_{it}\right)!}\right]^{-1} \tag{10}$$

$$= \frac{\left(\Sigma_{t=1}^{T_i} n_{it}\right)!}{\Pi_t n_{it}!} \Pi_t \left[\frac{\lambda_{it}}{\Sigma_{t=1}^{T_i} \lambda_{it}}\right]^{n_{it}} . \tag{11}$$

Note that λ_{it}^* becomes λ_{it} as α_i cancels out (as well as any other time-invariant explanatory variables). By defining $p_{it}(\beta) = \lambda_{it}/\Sigma_{t=1}^{T_i} \lambda_{it}$, this gives the multinomial distribution with a log-likelihood of

$$\ell(\beta) = \sum_{i=1}^{N} log \, \Gamma\left(\sum_{i=1}^{N} n_{it} + 1\right) - \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left\{log \, \Gamma(n_{it} + 1) - n_{it} \, log \, p_{it}(\beta)\right\} . \tag{12}$$

In essence, the fixed-effect procedure looks at the shares of total enlistments recruited in each period as a function of the changes in the values of the explanatory variables. Unobserved variations in productivity as well as time-invariant variables cancel out and cannot be estimated, which is one of the costs of using the fixed-effect, or multinomial, model. Estimating the time-varying variables, however, will demonstrate whether there is any significant difference between the random- and fixed-effect specifications.

The results for the multinomial model are presented in table 4. Standard errors were estimated using the Gradient method and the matrix of second derivatives of the log-likelihood function. The estimated effects of experience are slightly smaller than those obtained in the basic and random-effects models. The population coefficient is larger and the unemployment effect is now positive, but both variables still have much smaller than expected effects. The impact of SAM recruiting is similar in all three models.

Table 4. Fixed-effects Poisson estimates for SELRES enlistments

	Parameter estimate	Asymptotic standard errors	
		Hessian	Gradient
EXP	0.0599	0.0020	0.0045
EXP2/100	−0.2339	0.0117	0.0267
EXP3/10,000	0.2845	0.0193	0.0441
Population	0.1670	0.0141	0.0335
URATE	0.0024	0.0026	0.0059
SAMs	−0.0621	0.0029	0.0070

Log likelihood = −18,089.983

NOTE: There are 9,730 observations.

As an overall critique of the model, Hausman's specification test in [21] was estimated. Comparing the results for tables 3 and 4 using the Hessian estimates of the covariance matrices yields a test statistic of 80.68, which is distributed as x_6^2 under the null hypothesis of no correlation. The value of the test statistic far exceeds the critical value of 16.8 at the 1-percent level of significance. It appears that better recruiters are more likely to remain recruiters and therefore to have higher than average levels of experience through a selection effect. This will not only invalidate the random-effects specification, but also cause a bias in the estimated experience coefficients [3, 4].

Additionally, a Pearson chi-square statistic was computed. This statistic

$$X^2 = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \frac{\left[n_{it} - \left(\Sigma_t n_{it} \right) p_{it}(\hat{\beta}) \right]^2}{\left(\Sigma_t n_{it} \right) p_{it}(\hat{\beta})}$$

(13)

obtains a value of 11,466 on 8,948 degrees of freedom.[1] As before, this is a highly significant value, although it should be interpreted cautiously.

It seems, therefore, that the data still suffer from some over-dispersion even with the inclusion of fixed effects. One convenient way to deal with this residual over-dispersion is to use a quasi-likelihood approach (e.g., [22, 25]). Instead of assuming a complete

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1. Assuming the model is true, the asymptotic (as the $\Sigma_t n_{it}s$ increase) distribution of X^2 is chi-square with degrees of freedom given by the number of multinomial cells minus the number of parameters minus the number of recruiters [24].

distribution for the $N_{i1}, \ldots, N_{it_i}$, given $\Sigma_t n_{it}$ (such as the multinomial), only the mean and covariance are specified. One possibility is

$$E\left[N_{it} | \Sigma_t n_{it}\right] = \left[\Sigma_t n_{it}\right] p_{it}(\beta)$$

$$COV\left[N_{it} | \Sigma_t n_{it}\right] = \sigma^2 V \ ,$$

(14)

where V is the covariance matrix for a multinomial observation and σ^2 is a variance inflation factor. The matrix V has diagonal elements $n_{it} p_{it}(\beta)[1 - p_{it}(\beta)]$ and off-diagonal elements $-n_{it} p_{it}(\beta) p_{is}(\beta)$. Since the total number of recruits is fixed, it makes sense that the monthly $N_{it}s$ are negatively correlated. This specification retains the multinomial mean but inflates the multinomial variance by σ^2, thereby compensating for the over-dispersion.

An advantage of the quasi-likelihood approach is that explicit assumptions about the conditional distribution of the $N_{it}s$ are avoided. Only the first two moments need be specified. Quasi-likelihood provides an alternative to parametric methods for dealing with over-dispersion, such as the models in [14]. The models in [14] incorporate both recruiter effects and over-dispersion by either conditioning on the $\Sigma_t n_{it}$ and assuming that conditional on $\Sigma_t n_{it}$ the $N_{it}s$ are random variables, or by assuming that the $N_{it}s$ have nested random effects. For the recruiters, the nested random effects correspond to the assumption that each λ_{it} is random with a parametric distribution and that there is a random parameter for each recruiter that follows a parametric distribution as well. Since the assumed distributions are for unobservable random variables, direct verification of the assumed distribution is difficult. Quasi-likelihood avoids such assumptions. A drawback with the quasi-likelihood approach is that, in some sense, it merely acknowledges the over-dispersion without trying to explain it. Attempts to explain over-dispersion (e.g., with other explanatory variables) should be made. If, however, the chosen model still has over-dispersion, the quasi-likelihood approach provides a way to acknowledge this fact and to reduce the unwarranted precision of the parameter estimates.

Reference [22] discusses estimating parameters of a quasi-likelihood model. For the specification given in equation 14, quasi-likelihood estimates are the same as the maximum likelihood estimators of the multinomial model. In fact, whenever the mean and covariance structure match that of a density in the exponential family (save for the over-dispersion parameter σ^2), the quasi-likelihood estimates are the maximum likelihood estimates. An estimate of σ^2 is given by adjusting the Pearson chi-square statistics by its degrees of freedom: $\tilde{\sigma}^2 = X^2/d$, where d is the degrees of freedom.

Reference [26] shows that $\tilde{\beta}$ is asymptotically normal with mean β and covariance matrix $\sigma^2 \left[d^2 \ell(\beta)/(d\beta_j)(d\beta_k)\right]^{-1}$, which is the asymptotic covariance matrix for the multinomial distribution times the variance inflation factor. Therefore, in this model the quasi-likelihood approach relative to the multinomial model results in an increase in the variance of the estimates. For these data, $\tilde{\sigma} = \sqrt{11,466/8,948} = 1.13$ and none of the estimated effects of table 4 becomes insignificant.

The fact that the recruiting market condition variables—population and unemployment rate—do not have a strong impact in any of the above specifications is

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puzzling. Some previous research using aggregated data from this sample found a similarly weak impact of these variables until fixed geographic effects were included. The probable cause of these results is the existence of persistent differences in affiliation behavior among otherwise similar states. Sources of such differences are variations in economic opportunities not reflected in the unemployment figures, or differences in regional preferences for military service. Other institutional factors that may be important are the types of jobs available in the local reserve units and the quality of leadership of the reserve center Commanding Officer. Once the individual recruiter totals are conditioned upon, however, any time-invariant effect cancels out. For these data, only 4 percent of the recruiters sign up recruits in more than one state. Largely, state effects are nested within recruiter effects and the conditional approach should accommodate both state and recruiter effects.

CONCLUSIONS

Three models of individual recruiter productivity were derived and estimated in the preceding sections. Although the model estimates sometimes differed, several conclusions can be made. First, the effects of experience in a specific job have a very strong impact during the first two years and are relatively flat thereafter. Second, controlling for experience, recruiters in higher pay grades are more productive, thereby indicating that success in recruiting is correlated with the factors affecting overall success within the Navy.

The estimated effects of education are ambiguous, which is perhaps not too surprising in an occupation that requires sales rather than analytical skills. There appears to be little difference between high school graduates and non-graduates, but recruiters with college degrees are the least productive of all. The most likely explanation for this is selection bias, where the least productive individuals either do not make it to the senior grades required for recruiting duty, or do not remain on recruiting duty. The impact of this selection process will be greatest for non-high school graduates, with the result that only the best non-graduates become recruiters.

Individual heterogeneity is important, whether it is analyzed as a fixed or random effect. The magnitude of the individual effects is substantial, with an estimated population variance of 0.17. The individual effects act proportionally on mean productivity, which implies that enormous differences exist in expected productivity between good and bad recruiters. As in many economic applications, the individual effects are correlated with individual characteristics.

Although many of the variables analyzed have significant effects, the dominant factor is experience on recruiting duty. Figure 3 shows the total cumulative effect of experience on productivity.[1] It shows that recruiters with two years of experience are about twice as productive as new recruiters. This result emphasizes the loss associated with the departure of experienced recruiters, whether due to separations from the service or reassignment. Figure 4 illustrates the marginal impact of an additional month of experience on productivity. Both figures show similar profiles for all three models. The

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1. The predicted increase in productivity for recruiters with over 40 months' experience is due to the small number of observations and the cubic specification used to approximate the effects of experience. Therefore, the results at those experience levels should be viewed skeptically.
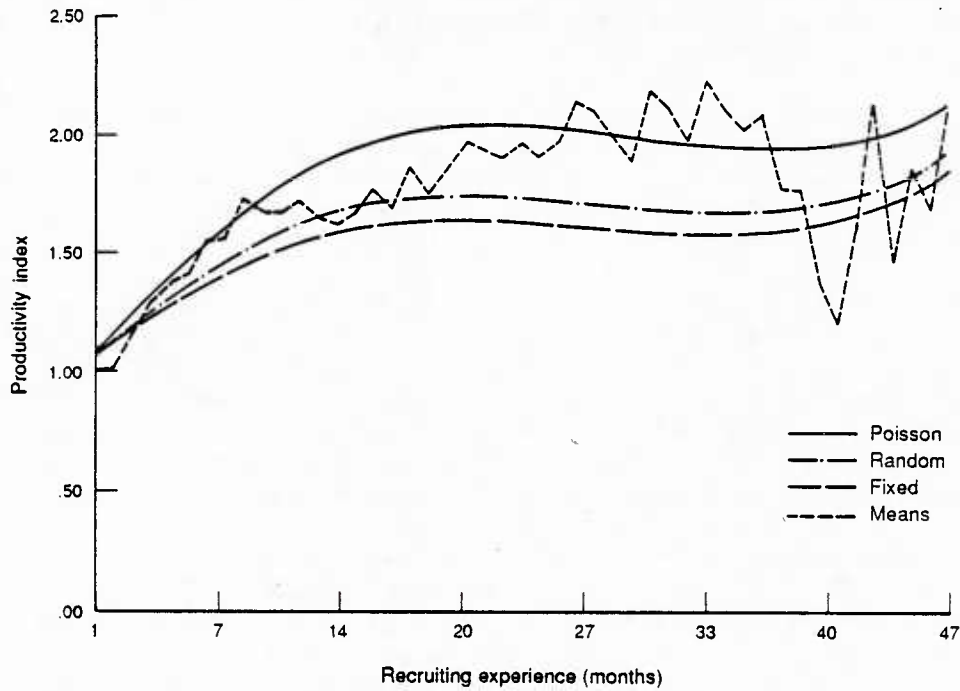
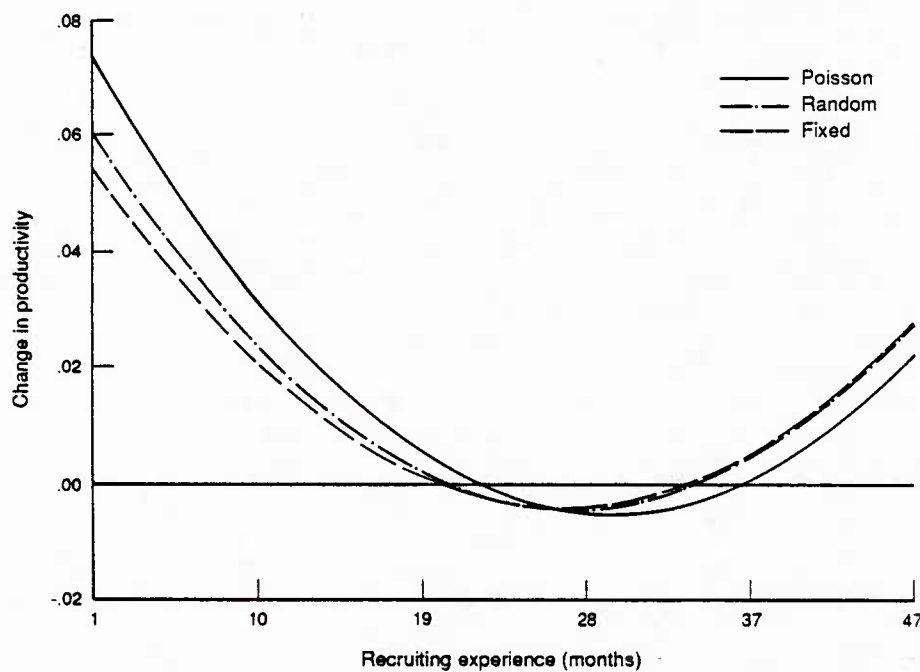**Figure 3.** Recruiter experience profiles

Figure 4. Marginal experience effects

basic Poisson model exhibits the strongest and most persistent effects of experience. The random and fixed effects, which allow for heterogeneity, are quite close; the fixed-effect model has the smallest, although still strong, impact.

It is interesting to note that, as in studies of earnings [3, 4], correcting for heterogeneity lowers the estimated effect of experience. Neglecting heterogeneity results in biased estimates due to the correlation between the individual effects and the experience variables. As in job-matching models, low productivity recruiters leave, while their more productive colleagues remain.

The conclusion of the analysis—that most of the growth in productivity occurs during the first year in the job and all of it during the first two years—has an interesting counterpart in the analysis of wage growth. Reference [27] finds substantial wage premiums offered to workers with one year of tenure, but little growth thereafter. Reference [4] estimates a similar effect in a substantially different data set. If the learning curve estimated in this sample is at all typical, these results provide a productivity-based argument for discontinuous tenure effects on wages.

These estimates pertain to only a small occupational group, and it is unclear how many of the findings can be extrapolated to the general population. The effects of recruiting-duty experience, for instance, primarily indicate the degree of on-the-job training needed to become fully proficient as a recruiter. Alternatively, the positive impact of a higher pay grade on productivity, which reflects a combination of general experience and matching effects, supports the hypothesis that more experienced workers are more productive, as well as better paid. The estimated effects, however, are not large enough to explain the earnings differential. The results of this study do highlight the importance of examining changes in job assignments when studying the effects of experience on productivity or earnings. For tasks with a significant learning period, time in a particular assignment is likely to have a far more important impact on productivity than time with the employer.

Among the disappointing results of this study was the inability to incorporate location effects into the analysis. The estimated effects of unemployment and population size are implausible, and future research should attempt to find a method for estimating those effects more precisely. Another intriguing topic for further research is to determine the extent to which more productive recruiters can be identified early in their careers; that is, to determine how many months are needed before it can be ascertained whether an individual is a high or low productivity recruiter. Some research in [28] indicates that recruiter quality may be detected early in a recruiter's tour. Further investigation may also provide some insight into whether productivity differences among recruiters are permanent, or instead tend to converge over time, perhaps due to learning or incentive effects.

The statistical methodology used in this paper began with a basic Poisson model and considered two generalizations of that model. Recruiter effects are important and if the variation in recruiter ability is of interest, the random-effects model is an appropriate procedure to consider. If recruiter and time-constant effects are not of primary interest, or the random-effects model seems implausible, the multinomial model provides a method to control for the recruiter effect while making fewer assumptions than the random-effects model. Finally, the quasi-likelihood procedure provides an easy method for

reducing unwarranted precision of parameter estimates. For these data, little changed with the quasi-likelihood approach. When over-dispersion is more severe, the application of quasi-likelihood would have a more pronounced change.

Further refinements of the quasi-likelihood approach are possible. The mean and covariance structure given in equation 14 assumes that the correlation between N_{it}, N_{is} for any two months does not depend on how close t and s are. The propriety of this assumption can be examined empirically. The first- and second-order autocorrelations of the monthly multinomial residuals are 0.15 and 0.01, respectively. The third through tenth are about -0.07. These correlations suggest that, even after a recruiter's individual effect has been conditioned out, what occurred during the last month or two affects productivity. Covariance matrices are discussed in [29] in the context of quasi-likelihood, which allows structures more general than that given by equation 14. The results in [29] do indicate, however, that inference results are somewhat robust with regard to specification of the covariance matrix. For simplicity, such refinements were not pursued in this paper.

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