NBER WORKING PAPER SERIES

TENURE AND OUTPUT

Kathryn Shaw
Edward P. Lazear

Working Paper 13652
http://www.nber.org/papers/w13652

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2007

Forthcoming, Labour Economics, 2007. We thank John Abowd, Joe Altonji, Avner Ben-Ner, Nicolas Williams, and referees for their suggestions and thank participants for meetings of the Society of Labor Economics and the ASSA meetings. We thank Valentin Agafonov and Diane Lee for excellent research assistance. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

Tenure and Output
Kathryn Shaw and Edward P. Lazear
NBER Working Paper No. 13652
November 2007
JEL No. J01,J24,J31,J33

ABSTRACT

A key tenet of the theory of human capital is that investment in skills results in higher productivity. The previous literature has estimated the degree of investment in human capital for individuals by looking at individual wage growth as a proxy for productivity growth. In this paper, we have both wage and personal productivity data, and thus are able to measure of the increase in workers' output with tenure. The data is from an autoglass company. Most of production occurs at the individual level so measures of output are clear. We find a very steep learning curve in the year on the job: output is 53 percent higher after one year than it is initially when hired. These output gains with tenure are not reflected in equal percentage pay gains: pay profiles are much flatter than output profiles in the first year and a half on the job. For these data, using wage profiles significantly underestimates the amount of investment compared to the gains evident in output-tenure profiles. The pattern of productivity rising more rapidly than pay reverses after two years of tenure. Worker selection is also important. Workers who stay longer have higher output levels and faster early learning.

Kathryn Shaw
GSB, Littlefield 339
Stanford University
Stanford, CA 94305-5015
and NBER
kathryns@gsb.stanford.edu

Edward P. Lazear
Graduate School of Business
and Hoover Institution
Stanford University
Stanford, CA 94305-5015
(on leave)
and NBER
lazear@gsb.stanford.edu

A key tenet of the theory of human capital is that investment in skills results in higher productivity, which is reflected in higher wages. The theory has spawned an enormous literature that estimates wages as a function of the workers' experience and job tenure. Wage increases with tenure (as opposed to general experience) are taken as evidence of firm-specific skills. As other models of wage determination entered the interpretations of wage regressions, the literature has produced estimates of the degree of firm-specific investment that differ markedly across the different estimation methods and data sets.[1] However, this literature has no direct evidence of learning on the job. In this paper, we use measures of the increase in workers' output with tenure as evidence of the degree of learning on the job.

Though a segment of the human capital literature is aimed at determining the pattern of investment in human capital (general or specific), there are several additional questions that are of interest in their own right, and also that contaminate our ability to estimate the pure returns to human capital using wage regressions. The secondary questions are: what are the returns to pure search, what are the returns to match quality, and to what degree do wage profiles slope upward as a means of inducing higher effort or greater investments in firm-specific skills? The point of using output regressions is that we can interpret the increased output with tenure as learning, separating the effects from other explanations of wage growth that are not directly related to productivity, especially during early years on the job.

Our goal is to use data on the actual output of individuals to estimate the output-tenure profile. The data are from Safelite, an autoglass company. The company has collected data on individual output, measured by windshields installed, for each worker over a period of as much as 1 ½ years.[2] Here, we use these data to estimate the effects of tenure on output, or the learning curve of individual employees. Because we do not have information on worker output in other firms, we cannot distinguish between the effect of learning on general or firm-specific aspects of productivity. But we do know that our

---

[1] See Altonji and Williams (2005) for a recent review and updated results. See also Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), Hutchens (1989).
[2] This is the data set used by Lazear (2000) to estimate the effects of piece rate pay on performance.

effects are true productivity effects and do not reflect selection. Selection is important, but because we have individual data on productivity over a portion of the career, we can distinguish selection effects from learning effects. Specifically, we can determine the amount by which selecting the right employees raises the learning curve of employees. Finally, we see how much the wage profile (or the wage-tenure relationship) diverges from the output-tenure relationship under two payment regimes – the payment based on hourly wages, and the payment based on piece rate pay.

The use of the Safelite data on windshield installation by individuals has both advantages and disadvantages. First, it is only possible to estimate the learning curve of individuals when the work is individual, rather than team-based.[3] Second, we must be able to measure output. Given these two objectives, we are confined to data sets in which production is a fairly simple process, as in Safelite. Given such simplicity, the learning curves estimated with this data are likely to be steeper and shorter than those that would be estimated for data on more complex jobs. Thus, a drawback of the data is that it is surely an underestimate of the returns to skill development across occupations. And given the simplicity of the production function, the incentive pay schemes that accompany this production are also likely to be simpler than those for more complex or sophisticated skills or jobs. The primary advantage is that output is well defined and, as a result, the effects that are estimated have straightforward interpretations.

We describe the data next, followed by the output regressions. We then compare the output regressions to pay regressions. And finally, we estimate models in which we can assess the degree to which selecting high ability workers affects the learning curve of the firm.

[3] In a team based setting, we would aim to estimate the average learning curve of individuals in the team, which would also be of interest. However, given that most teams are composed of individuals of different experience or tenure levels, it would be difficult to estimate a true learning curve for a typical team member.

1. The Data

The data are on the output and pay of individual workers in the Safelite corporation which installs windshields in cars at peoples' homes and in its retail shops.

Safelite Glass Corporation is located in Columbus, Ohio and at the time was the country's largest installer of automobile glass, a process in which the employee typically drives a truck to the customer's location and installs a new windshield in their car. In 1994, Safelite, under the direction of CEO, Garen Staglin, and President, John Barlow, implemented a new compensation scheme for the autoglass installers. Until January, 1994, glass installers were paid an hourly wage rate, which did not vary in any direct way with the number of windows that were installed. During 1994 and 1995, installers were shifted from an hourly wage schedule to performance pay—specifically, to a piece rate schedule. Rather than being paid for the number of hours that they worked, installers were paid for the number of glass units that they installed.

Staglin and Barlow changed the compensation scheme because they felt that productivity was below where it should have been. Productivity could have been raised by requiring a higher minimum level of output under a time rate system. If all workers had identical preferences, this would have worked well. Given differences in work preferences, a uniform increase in required output, coupled with a wage increase, would not be received in the same way by all workers. In particular, the lower- output workers would find this more burdensome than the higher output workers. In order to avoid massive turnover, the firm adopted a piece rate schedule, which allowed those who wanted to work more to earn more, but also allowed those who would accept lower pay to put forth less effort.

Safelite has a very sophisticated computerized information system, which keeps track of how many units of each kind that each installer in the company installs in a given week. Safelite provided monthly data. Since PPP (Performance Pay Plan) was phased in over a 19-month period, many workers were employed under both regimes. Thus, data on individual output are available for most installers both during the hourly wage period and during the PPP period. As a result, we can examine workers under either (or both) of the two pay regimes.

Our data are for the period of January 1994 through July 1995, during which time the firm moved from hourly pay to piece rate pay gradually and randomly. The piece rate plan had a guaranteed minimum pay equal to $11 per hour, but workers were paid about $20 per windshield above the minimum pay. They installed about 3 windshields per day on average. The dataset also contains the workers' date of hire, and thus their tenure level. The complete dataset contains 29,837 monthly observations on 3,707 workers. We reduce the data to 8,527 observations on 1,225 individuals when we follow only those who started work after 1994, and thus have complete observations on output from their start date. Variable means are in the appendix.

2. The Effects of Tenure on Output

Our emphasis is on the estimation of learning curves for employee productivity. In these data, we cannot distinguish between occupational skills or industry skills and firm-specific skills because our data are only for one company. In principle, the activity of installing windshields is an occupational or industry skill – it can be transferred to other firms (Neal, 1995, Shaw, 1987). The market for these skills is thin (Lazear, 2005), but workers do move from one windshield company to another and sometimes back again. We do not have data on individual employee's age or years of experience. In sum, we model learning curves that to a degree combine firm-specific skills and occupational skills.[4]

The output regression to be estimated is as follows:

[4] The learning curve literature has typically focused on learning at the plant or firm level (Benkard, 2000; Argote, Beckman, and Epple, 1990), or on wages and productivity for groups of employees (Hellerstein and Neumark, 1999, 2004; Hellerstein, Neumark and Troske, 1999; Van Biesebroeck, 2005).

(1) $\ln\left(\text{output}\right)_{it} = \beta_0 + \beta_1 \text{Tenure}_{it} + \beta_2 \text{Tenure\_After\_Piece\_Rate}_{it} + \beta_0^P \cdot \text{Piece\_Rate}_{it}$

$$+ \gamma X_{it} + \alpha_i + \varepsilon_{it}$$

where i=individual, t=month, $\mathbf{X}_{it}$ is a vector of time controls (month and year), α_i is person-specific ability, and ε_{it} is the random error term. The learning curve implies that $\beta_1>0$. We also introduce the possibility that learning curves are different (or more rapid) under the piece rate pay scheme, and thus that $\beta_2>0$.

Estimating the fixed effects regression of (1), initially we use only the data when we have each individual's complete record of performance from the time he is hired up to a potential of 19 months of data (the mean values of the variables are in the Appendix). As a result, the estimates of learning effects are presented initially (and primarily) for the initial period on the job. The first regression results are in Appendix Table B. We plot the results in Figure 1.

In Figure 1, we follow people over their *career profiles* with Safelite to see how learning varies before and after the piece rate pay plan is introduced. That is, there are two types of people. The first type is those who are "new entrants to the firm hired under the hourly pay regime" and who then may or not stay with the company when the pay regime shifts to piece rate pay. The second type is those who are "new entrants to the firm hired under piece rate pay" and thus always work under the piece rate pay regime while at the firm. Figure 1 is based on the fixed effects output regression of Appendix Table A2

The primary finding is that learning is pronounced. For workers hired under the original hourly pay plan, during their first month of tenure, workers are 42% less productive than they will be one year later. For workers hired under the piece rate plan, workers start at higher productivity levels and are 36% less productive in their first month of tenure than they are at month 12. In Table 1 below we will estimate a more flexible functional form that divides the sample into pay plan types. We form the remaining tables in the paper based on that functional form.[5]

It is not surprising that learning is important, especially during the first few months on the job, but the fact that it can be documented by detailed measures of output and that it is so pronounced is novel. At least in this simple production process, workers appear to learn a great deal during their initial period of employment. Human capital formation is real. Selection effects may be important (as will be seen below), but the effect that we estimate here is not a selection effect. It is the true effect of learning for those workers who remain on the job during a given period of time. Selection is relevant insofar as the population on which we estimate the data is not the population of initial employees since some leave. It is best thought of as the learning effect, conditional on remaining with the firm. But our estimates do not suffer from the problem of picking up productivity growth that would be seen because the least able workers leave the firm. That upward bias in the learning effect is cleaned out because we estimate our tenure effects by measuring a *given* worker over his work career. When hourly workers move to the piece rate pay plan, they are on average 18 percent more productive (as measured by PieceRate dummy).[6] Thus, the stayers under the piece rate were fully skilled prior to the introduction of the piece rate, but simply were not exerting as much effort under the hourly pay scheme.

While the steep productivity-tenure profiles are labeled "learning" curves, these learning curves could result from increasing effort as well as increasing skills. Piece rate pay workers always have higher productivity than hourly paid and a portion of this productivity premium is due to greater effort (Lazear, 2000). The steeper productivity-tenure profiles of the hourly paid could be due to rising effort levels on the first six

[5] The fixed effects regressions provide the slopes of these learning curves, but not the initial output levels. The starting output levels are the mean values for the data set. New hires under the hourly plan have an initial output level (in the first month) of 1.34 windshields, while new hires under the piece rate plan have an initial output level of 2.12 windshields. These output levels are very significantly different from each other.

[6] This is comparable to that estimated in Lazear (2000). In the fixed effects estimation, the effect of the piece rate plan is estimated off the original hires who change plans, not the new hires under the piece rate.

months, not just rising skill levels. Effort could rise as they see that workers who are not fired earn much more with tenure at Safelite (see pay regressions below).

3. Comparing the Wage-Tenure Profile to the Output-Tenure Profile

The effects of tenure on output are typically inferred from the wage-tenure profile. Thus, in this section, we compare the wage-tenure profile to the output-tenure profile. To focus on the different pay regimes, we divide the data into two data sets: one with those workers currently paid hourly and hired during the hourly pay regime "(N=2709 worker-months); and another of those workers currently paid piece rate but hired under either plan (N=5808 worker months).

In the first year, the output gain is 62% for workers under the hourly pay plan (Table1, column 5) and 37% for workers under the piece rate pay (Table1, column 7) for a weighted average across plans of a 53% output gain. These gains occur in the first twelve months on the job.[7]

Our results show that the wage-tenure profile does not proxy the output-tenure profile very well. The estimated pay-tenure profile is completely flat under the hourly pay scheme (Table 1, fixed effects column 1). Thus, using a typical payment plan, such as hourly pay, if the wage-tenure profile were used to infer the productivity profile, it would imply that there is no learning or no performance gain with tenure over the first 19 months with the firm. In truth, when we measure the output-tenure profile for these workers (Table 1, fixed effects column 5) we observe that there is a pronounced gain in output with tenure. Thus, in the case of a simple production function such as this, wage-tenure profiles are considerably flatter than output-tenure profiles, so wages are not a good proxy for output in estimating productivity gains from tenure, at least during the first few months on the job.

[7] For all of the regressions of Tables 1 and 2, when the hourly and piece rate samples are combined in one regression, F-tests show that the estimated tenure profiles (for output or wages) differ significantly between the hourly and piece rate regimes (results available on request).

We might expect the wage-tenure profile to be flatter under the hourly pay regime because wages would be adjusted infrequently: often wages are adjusted at three or six month intervals on a job. It is this very lack of wage adjustment that makes hourly wages a poor proxy for productivity.

For workers working under the piece rate scheme, the pay-tenure profile more closely reflects the output tenure profile (columns 3 and 7).[8] Any other result would be surprising given the payment scheme is piece rate pay, which relates pay directly to output. But note that the pay profile is less steep than the output profile: the piece rate plan has a guaranteed minimum pay, which dampens the relation of pay to output. Thus, even under piece rate pay, pay gains are a poor proxy for output gains with tenure. And in typical jobs, hourly pay is the norm, where profiles are even flatter than with piece rate plans.

In sum, if we were to use pay as a proxy for output during the first 19 months on the job, we would underestimate the degree of learning on the job. In a later subsection below, when we look at older workers for whom we do not observe the early learning phase of employment, we will see that the pay profile becomes steeper than the productivity profile at higher tenure levels.

4. Screening and Self-selection of Workers Based on Ability

These data also provide some evidence that the value to the firm of selecting the right (or most productive) workers can be quite high. In Figure 2, we compare the *pay-tenure* profiles of the fixed effects regressions to OLS regressions. Selection effects are very sizable in the pay-tenure profile of the hourly pay regime with OLS—the estimated OLS wage profile is very steep (Table 1, column 2). Given the completely flat profile of the fixed effects estimation for the pay regression, the steepness of the pay-tenure profile arises entirely from selection effects. For any newly hired worker, there is no pay

[8] Note that Lazear (2000) shows that piece rate pay is more profitable than hourly pay. In contrast, Freeman and Kleiner (2005) show that hourly pay is more profitable in shoe production even though piece rate pay is more productive.

increase with tenure, but across workers, young workers who are more likely to quit or be fired have much lower pay than do long tenure workers within their first year of experience with this firm. There is also a gap between the OLS and fixed effects profiles for piece rate paid workers, but it is not as sizable, due probably to better selection under piece rates and due to pay that is a function of output.

Similarly, Figure 3 shows that the selection effects are also large in the *output-tenure* profiles for hourly paid workers and for piece-rate paid workers. As shown in the Figure (comparing columns 1 and 2 of Table 1), the output-tenure profile is over 50% steeper in the OLS regressions in the early years of tenure during the learning phase—a difference due entirely to the quitting of poor quality workers who are initially less productive. Comparing the profiles for pay (Figure 2) to output (Figure 3), the worst (lowest) paid; workers leave rapidly and the higher paid remain as tenure grows.

Overall, we find that the firm is likely to be using two methods to screen or select workers. First, our data shows they are able to sort workers by skills prior to hiring. We conclude this because they do not pay all workers the same starting salary. The standard deviation of starting daily pay for hourly workers is $19.2, given a mean of $70.8; the standard deviation of starting pay (in the first month) for piece rate pay is $19.7, given a higher mean of $84.7. The comparable productivity mean (standard deviation) of windshields per day are 1.75 (1.20) and 2.17 (1.58).[9] Note that under both regimes, starting pay varies considerably across new hires, but it varies less than starting productivity. However, pay and productivity are highly correlated in the first month: The correlation between the starting pay and starting output of workers under the hourly pay plan is .44, and under the piece rate plan is .62 (where, of course, the output-pay correlation is higher because piece rate pay includes a fixed base and a pay for output component). Thus, the firm can assess skills, and does pay workers differentially for skills. Similarly, during the hourly pay regime they are likely to reject some workers lacking potential skills (especially under the hourly pay plan given pay independent of

[9] The sample sizes are 688 and 409 new hires under hourly and under piece rate pay. For all workers the mean (s.d.) of pay is 78.4 (21.85) (N=2444) and 94.2 (25.9) (N=5658). Comparable productivity measures are 2.37 (1.24) and 3.11 (1.41).

output, when screening up-front is more important). The firm does see whether the worker has prior windshield installing experience (that we don't measure), and that may account for their ability to sort workers up-front.

Second, the firm is selecting or screening through quits or fires, as when low-performing workers self-select out or the firm fires them. This is obvious because the OLS wage profile is much steeper than the fixed effects profile: the poor performers with low starting wages leave at much higher rates than the higher paid workers, so there appears to be a positive wage profile when there is not (for hourly pay). The same is true for productivity: the poor performers leave and the better performers stay, though the selection effects are greater for wages than productivity.

In sum, the firm is using both up-front screening and later sorting to select workers. A 1 though the firm is screening up-front for skills, they also appear to be hiring low quality workers whose pay exceeds performance relative to high quality: pay and productivity are not perfectly correlated across individuals. However, the higher pay-output correlation of .62 in the piece rate pay regime suggests pay is closer to performance for piece rate pay.[10] The reason the firm does not screen better up-front is likely to be twofold: it is difficult to assess skills prior to hiring; and it is easy to fire. In contrast, if we were looking at more skilled jobs, such as computer programmers, we would expect to find that the firms spend much more money on the screening process up-front, because there is more information on which to screen and because the cost of firing is greater. We return later to this selection issue when we look at the quality of leavers.

5. Paying for the Investments and Earning Rents

The classic model of firm-specific investment always asks the question, does the worker and the firm split the costs and returns to firm-specific skills? In the typical model of firm-specific skills, both the worker and firm invest, so the pay profile is flatter than the

[10] Note that with hourly pay, the correlation between starting pay and output could be negative even with careful sorting of workers: if the high-ability are investing more in skills, their current wage may be higher, but their current productivity lower, if the skills are entirely firm specific.

output profile: firms pay less than productivity as tenure grows. However, in an alternative incentive pay model, pay may exceed productivity with tenure because firms want to attract workers who will increase effort over time or accept the offer for future rewards. Because we have output and pay data, we can test these predictions while others have been unable to undertake these tests.

We find evidence supporting both models. As shown in Figure 4, during the first 19 months on the job, the pay profile is always flatter than the output profile, as theories of firm-specific investment would suggest. Thus, there could be sharing of investment costs and rents. However, we cannot see the amounts of investments, or the size of the rents earned, because we lack two key variables, the alternative wage, and the value of the output to the firm. Therefore, the figures in Figure 4 are drawn so that the pay and output profiles are normalized so they overlap (as shown, pay is divided by about 40 in each figure). Within the first nineteen months on the job, the relative flatness of the wage profile suggests there may be some splitting of the investments and rents, but lacking measures of the value of output or alternative wages we cannot confirm this (Oi, 1962; Becker, 1993; Lazear, 2005).[11]

However, we also find strong evidence that wages rise faster than productivity as workers get considerably older under the hourly pay regime. In Table 2, the full sample (new hires plus older workers of 29,412 worker-months) is used to estimate traditional wage tenure profiles and to compare them to output-tenure profiles. The X variables are years of tenure, tenure squared, and tenure-cubed, for comparability to other studies but our results are the same if we estimate the model with annual tenure dummies. By using annual measures of tenure, we know we are missing the productivity gains that occur in

[11] The wage growth is low in this firm relative to the typical gain to tenure across all occupations (Altonji and Williams, 2005). But the results for this low-paying occupation have some broader implications. The investment in firm-specific human capital could be considered a cost for the firm of hiring employees, in this firm and other firms. Though the learning curve is short here, the much lower productivity for four months can be a sizeable cost for the low-pay high turnover jobs. In the hourly pay regime, the firm appears to bear these hiring costs, though we cannot confirm this lacking data on prices and alternative wages. In piece rate pay, the position slopes of productivity and pay would suggest there is cost sharing. In any case, given sizeable performance gains, we discuss below how the firm might lower their heavy costs of investment by sorting workers more when hiring.

the first months of the first year of tenure, but for 73% percent of our sample, we do not have monthly starting data. Therefore, to better fit the model, we add one dummy variable for the first year of tenure (Tenure1=1) to show that productivity does have a non-linear jump up after the first year of learning.

As shown in Figure 5, output-tenure profiles based on fixed effects regressions show that productivity falls over the long run. Output-tenure profiles show that productivity peaks in the second year of tenure in both pay regimes, and then falls from 2.9 to 2 windshields per day for piece rate workers, and from 2.2 to 1.6 per day for hourly paid workers (see Figure 5C, which graphs the fixed effects regressions of Table 2). These fixed effects results that look at within-person performance, show that people appear to *decrease* their effort, or have other physical reasons why their productivity declines with tenure.

In contrast, pay-tenure profiles based on fixed effects regressions show that hourly pay rises with tenure over the long run, but piece-rate performance pay does decline with tenure after about four years (Figure B). In sum, a steep wage profile is used more in the hourly pay regime, where the pay-tenure profile is the only form of incentive pay. The pay profile is less steep in the piece rate plan, where incentives arise daily when pay is a function of performance. This might well be expected in standard models of wage policies.

Switching from the fixed effects regressions to OLS regressions, the OLS results for the pay-tenure profile for the hourly paid workers, show a very striking rise in pay that peaks at tenure year nine (Figure 5D). These OLS results combine selection with within-person wage growth. The average employee, who is looking at the average pay of people by tenure cohort, would surmise that there is a pronounced jump in pay with tenure. Thus, to the extent that pay is an incentive device, his reaction would be much stronger, and these OLS regression results may be the relevant results, rather than the fixed effects results, for a worker forming expectations of pay increases with tenure.

6. Selecting Workers with the Potential to Learn on the Job

Firms often state that when they select workers, one feature of ability that they look for is the ability to learn. In jobs with high degrees of firm-specific human capital investment, this should be especially true. Thus, the output regression of (1) should be amended to permit the coefficient on Tenure to be individual specific:

(2) $\ln(\text{output})_{it} = \beta_0 + \beta_{1i}\text{Tenure}_{it} + \boldsymbol{\gamma}\mathbf{X}_{it} + \alpha_i + \varepsilon_{it}$

Ability enters through the base-line output, α_i, and through the ability to learn, β_{1i}, where the i subscript on β_{1i} implies that each person i has their person-specific ability to learn as tenure grows. For simplicity, we dropped piece rate variables from (2), but in the regressions we permit the intercept and tenure coefficient to vary by pay regime.[12]

There are reasons why it would be illuminating to estimate what causes individual differences in learning curves. The coefficient on tenure in the regressions above is the average return to tenure across ability levels. It is the "treatment of the treated" effect: the average return for this company given selected ability or match quality levels. Conditional on the firm's current selection procedures, the mean tenure coefficient is unbiased. However, if there is significant variation in learning across individuals, it may be cost effective for the firm to improve its selection methods and thus increase learning curves.

[12] The ability to learn, β_{1i}, could be an individual-specific pure ability to learn or could reflect the quality of the match between the worker and the firm. A typical wage-tenure regression would introduce match quality in the error term: $\varepsilon_{it} = \varphi_{ij} + e_{it}$, where φ_{ij} is a fixed job-specific, j, quality of the match between the job and the worker. Since we have only one job that we observe, we cannot observe match quality. If the learning curve were due to match quality, then correlation $\rho(\varphi_{ij,}\ \beta_{1i}) > 0$. If the learning curve is a pure person-specific ability to learn, then $\rho(\varphi_{ij,}\ \beta_{1i}) = 0$. In our case, with data on only one firm for each person, the match quality feeds directly into the person effect, α_i and in the fixed effects regressions it neither biases the estimated tenure effect nor can it be identified. For a full discussion of the matching effect in the wage-tenure regressions, see Altonji and Williams (2005). In wage-tenure regressions across firms and individuals, the potential bias in the tenure coefficient from omitting the match quality is unsigned. A matching model (or model of 'experience-good search') implies that when workers take a job and then discover they are poorly suited to the job, they will leave quickly or have short tenure. In cross-sectional data, tenure coefficients pick up a combination of learning and sorting effects. Those who stay longer are not only more skilled as a result of what they have learned, but they also are likely to be better suited to their job, which is why they stay on it.

We can use (2) to estimate how much individual variation there is in the ability to learn. Assuming that the coefficient β_{1i} on Tenure is linear, then the first-differenced regression is:

$$(3) \qquad \Delta \ln(\text{output})_{it,\, t-1} = \beta_{1i}\,(\text{Tenure}_{it} - \text{Tenure}_{i,t-1}) + \boldsymbol{\gamma}(\mathbf{X}_{it} - \mathbf{X}_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1})$$

It is probably reasonable to assume β_{1i} on Tenure is linear in the first six months on the job. Because (Tenure_t - Tenure_{t-1})=1 for monthly increases in tenure, (3) becomes

$$(4) \qquad \Delta \ln(\text{output})_{it,\, t-1} = \beta_{1i} + \boldsymbol{\gamma}(\mathbf{X}_{it} - \mathbf{X}_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1})$$

The first-differences regression (4) is estimated with fixed effects for the subsamples of workers with the first five months under the hourly pay regime or under the piece rate pay regime, where we lose all individuals with tenure of only one month.[13]

There are very significant differences in individual learning curves for windshield production. In this regression, the fixed effects, β_{1i}, in the output growth regression of (4) contribute an additional 23 percentage points to the R-squared across all payment regimes (regression is not shown).

To put this in perspective, when we estimated the regressions earlier with fixed effects in the level of output and pay, we found that the omitted person-specific effects explain 55% of the variance in the hourly regime and 63% in the piece rate regime (Table 1). Thus, individual differences in learning could be a sizable portion of individual differences in pay levels.

[13] The regression can also be estimated in long differences, in which we difference (2) over the interval t-k to t, where k is a lag of up to five months, and then divide by k so that tenure is differenced out and the dependent variable is the average monthly growth in output: $\Delta \ln(\text{output})_{it,\, t-k}/k = \beta_{1i} + \boldsymbol{\gamma}(\mathbf{X}_{it} - \mathbf{X}_{it-k})/k + (\varepsilon_{it} - \varepsilon_{it-k})/k$.

Given these sizable individual-specific differences in learning, the firm may have significant gains to sorting workers on their ability to learn. We examine this potential by hypothesizing that there are two types of workers: stayers and leavers. We define the leavers as those who work less than six months at the firm.[14] In the output regressions of Table 3 a dummy variable for "leaver" is interacted with the tenure variables for the first five months of tenure (since leavers stay five months or less). The tenure*leaver interactions show that leavers learn at a significantly lower rate: the output-tenure profiles are flatter. These results are displayed in Figure 6, which graphs the predicted output-tenure profile for stayers under piece rate pay versus leavers. Leavers have lower starting productivity and somewhat lower rates of learning.

Given that the mean output and growth of output is lower for leavers than stayers, should managers do a better job of evaluating potential employees to exclude the potential leavers? If wages were equal to output and fixed hiring costs were low, there would be no reason for firms to screen carefully – firms would fire instead of screening new hires. Do leavers earn less than stayers? Table 4 contains the pay regressions that are comparable to the Table 3 output regressions. Leavers do not have lower growth rates of pay than stayers (in the fixed effects). We know leavers have lower starting pay. However, the starting pay of leavers is only 6% below that of stayers, but their output is 37% below in the first month in the hourly pay regime.

Thus, workers who leave within six months earn a much higher starting pay than their performance warrants compared to stayers. These results suggest that firms are doing some initial sorting based on potential performance, but that leavers are costly relative to stayers. Of course, the hiring of leavers and the high relative pay of leavers is optimal if the costs of screening for ability are high. Managers are weighing the costs of screening more carefully to avoid hiring "leavers" versus the costs of higher pay and the use of quits or layoffs to remove the low performing "leavers" after they are hired.

[14] Those with six months of tenure at the end of the data set are dropped from this sample.

7. Conclusion

On a simple job such as windshield installation, there is a very steep learning curve in the first year on the job: output is 53 percent higher after one year than it is initially. Our data show that these output gains with tenure are not reflected in equal percentage pay gains with tenure. During the hourly wage pay regime, there is no pay gain with tenure in the first 19 months on the job, and in the piece rate regime, the gain is modest relative to the output gain. Wage-tenure profiles are much flatter than output-tenure profiles during the initial year and one half on the job. The most important point is that these data reveal that wages profiles are not good proxies for output profiles. Using wage profiles significantly underestimates the amount of learning compared to the gains evident in output-tenure profiles.

For older workers, after the first two years of tenure, productivity declines with increased years of tenure. It would appear that "learning" on the job decreases. But since the type of work does not change, productivity depreciates either because workers skills depreciate with age, or effort declines. The slope of the pay-tenure profile matches the productivity-tenure profile for piece rate workers; both pay and productivity decline at high tenure. For hourly paid workers, pay rises at higher tenure we have no direct evidence to distinguish between deterioration of skills and effort, but think declining effort is the most likely explanation. It seems implausible that skills would decline so quickly. Boredom is a more reasonable explanatory factor.

The firm is using both up-front screening and later sorting to select workers. They screen for quality and pay accordingly. Starting wages and productivity are highly correlated. However, in theory, there is likely to be a tradeoff for firms facing expenditures on selecting workers: firms that have high turnover rates (due to firing or quits) are probably spending less up-front on careful hiring. We find evidence of this tradeoff in this firm. The output gains from weeding out lower quality workers in the first months on the job are very substantial: the fixed effects regressions have considerably flatter output-tenure and pay-tenure profiles than do the OLS regressions. The steeper OLS profiles show that firms are learning about ability and weeding out the less able, instead of hiring carefully up-front.[15] We confirm the importance of person fixed effects by looking at the quality of "leavers," who leave the job in less than six months, versus stayers. The leavers are lower quality workers than stayers. The leavers have lower starting output and lower growth of output on the job than stayers. The leavers also have lower starting pay and lower growth of pay, but the pay gap between leavers and stayers is much less than the output gap: leavers are costly relative to stayers. Should the firm pay more up-front to sort employees and avoid hiring the costly leavers? Given how much weeding out there is of workers after they are hired, the firm appears to find it more cost effective to spend less on up-front screening. However, in more skilled occupations where the costs of firing or quitting are greater, it may be cost-effective to spend more on hiring costs. Thus, when they are hired, the firm does sort leavers and stayers and pays leavers less, but it appears to be the case that this firm is hiring costly leavers because it is cheaper to screen them out later rather than screening them out during hiring. Instead, the firm hires workers across a broad spectrum of basic ability levels and those who don't perform are more likely to be fired or to quit.

[15] We refer to the learning curve here as learning and skills. But learning models often refer to the firm or worker learning about the worker's ability (Gibbons and Waldman, 2004).

REFERENCES

Abraham, Katharine G., and Henry S. Farber. 1987. "Job Duration, Seniority, and Earnings." *American Economic Review*, Vol. 77, No. 3 (June), pp. 278-97.

Altonji, Joseph G., and Robert A. Shakotko. 1987. "Do Wages Rise with Job Seniority?" *Review of Economic Studies*, Vol. 54, No. 3 (July), pp. 437-59.

Altonji, Joseph G., and Williams. 2005. "Do Wages Rise with Seniority: A Reassessment" *Journal of Human Resources*. 58(3), 370-397.

Argote, Linda, Sara Beckman, and Dennis Epple. (Feb. 1990). "The Persistence and Transfer of Learning in Industrial Settings," *Management Science.* 36 (2): 140-154.

Becker, Gary S. 1993. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Chicago, University of Chicago Press.

Benkard, Lanier. September 2000. "Learning and Forgetting: The Dynamics of Aircraft Production," *The American Economic Review*, 90 (4): 1034-1054.

Freeman, Richard B. and Kleiner, Morris M., "The Last American Shoe Manufacturers: Changing the Method of Pay to Survive Foreign Competition" *Industrial Relations*, April 2005, Vol. 44, No.2, pp. 307-330.

Gibbons, Robert and M. Waldman. Task-Specific Human Capital. *American Economic Review* 94 (2004): 203-07.

Hellerstein, J. K. and D. Neumark. 1999. "Sex, Wages, and Productivity: An Empirical Analysis of Israeli Firm-Level Data," *International Economic Review*, Vol. 40, No. 1, 95-123.

Hellerstein, J. K. and D. Neumark. 2004. "Production Function and Wage Equation Estimation with Heterogeneous Labor: Evidence from a New matched Employer-Employee Data Set," *NBER Working Paper*, No. 10325.

Hellerstein, J. K., D. Neumark, and K. R. Troske. 1999. "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations," *Journal of Labor Economics*, 17(3), 409-446.

Hutchens, Robert, M., 1989 "Seniority, Wages and Productivity: A Turbulent Decade," Journal of Economic Perspectives 3 (4), 49-64.

Lazear, Edward P. 2000. "Performance Pay and Productivity." *American Economic Review*, Vol. 90., No. 5: 1346-1361.

Lazear, Edward P., "Firm-Specific Human Capital: A Skill-Weights Approach" (June 2003). IZA Discussion Paper No. 813.

Neal, Derek. 1995. “Industry Specific Human Capital: Evidence from Displaced Workers.” *Journal of Labor Economics*, Vol. 13, No. 4 (October), pp. 653-77.

Oi, Walter Y.,1962."Labor as a Quasi-Fixed Factor," *Journal of Political Economy*, LXX, (6), 538-555(December).

Shaw, Kathryn. “A Formulation of the Earnings Function Using the Concept of Occupational Investment,” *Journal of Human Resources*, 19 (Summer 1984): 319-340.

Topel, Robert H., 1991. "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy* 99(1), 145-76 (February).

Van Biesebroeck, Johannes. 2005. “Wages Equal Productivity. Fact or Fiction?” Working Paper.

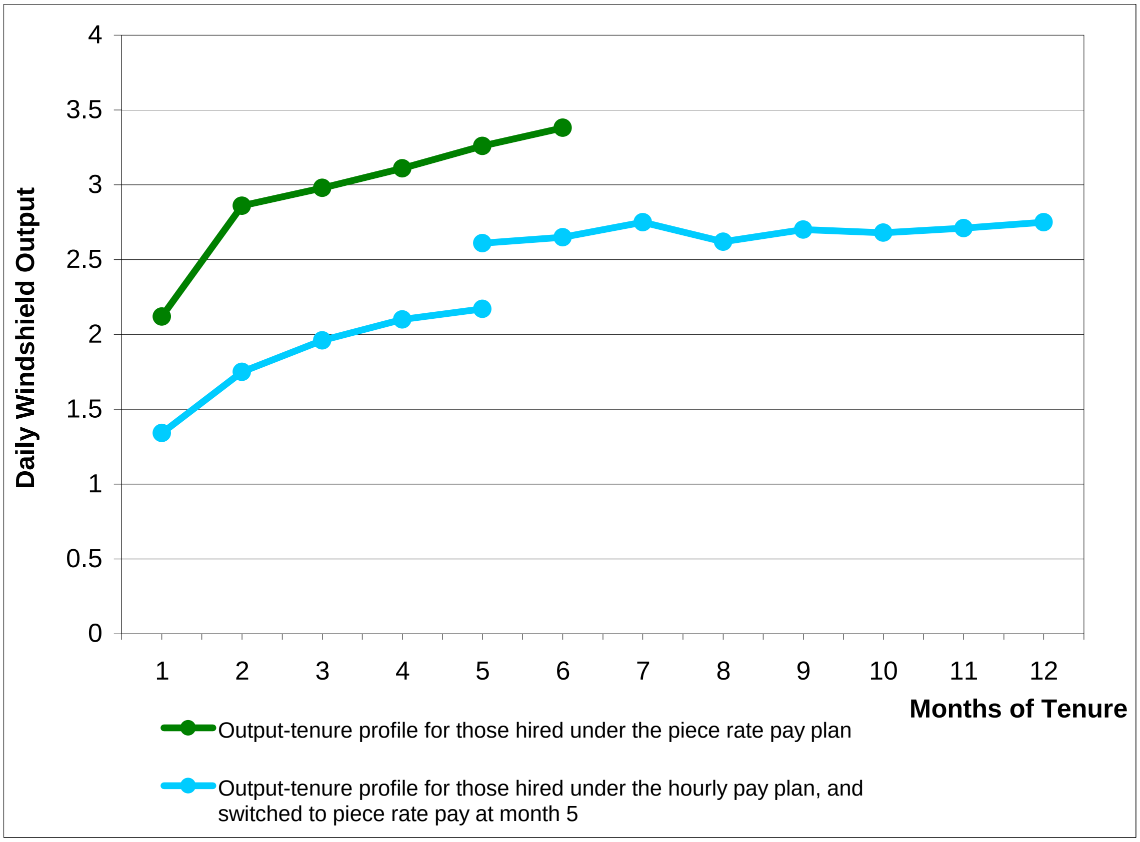

Figure 1: Predicted Output-Tenure Profiles

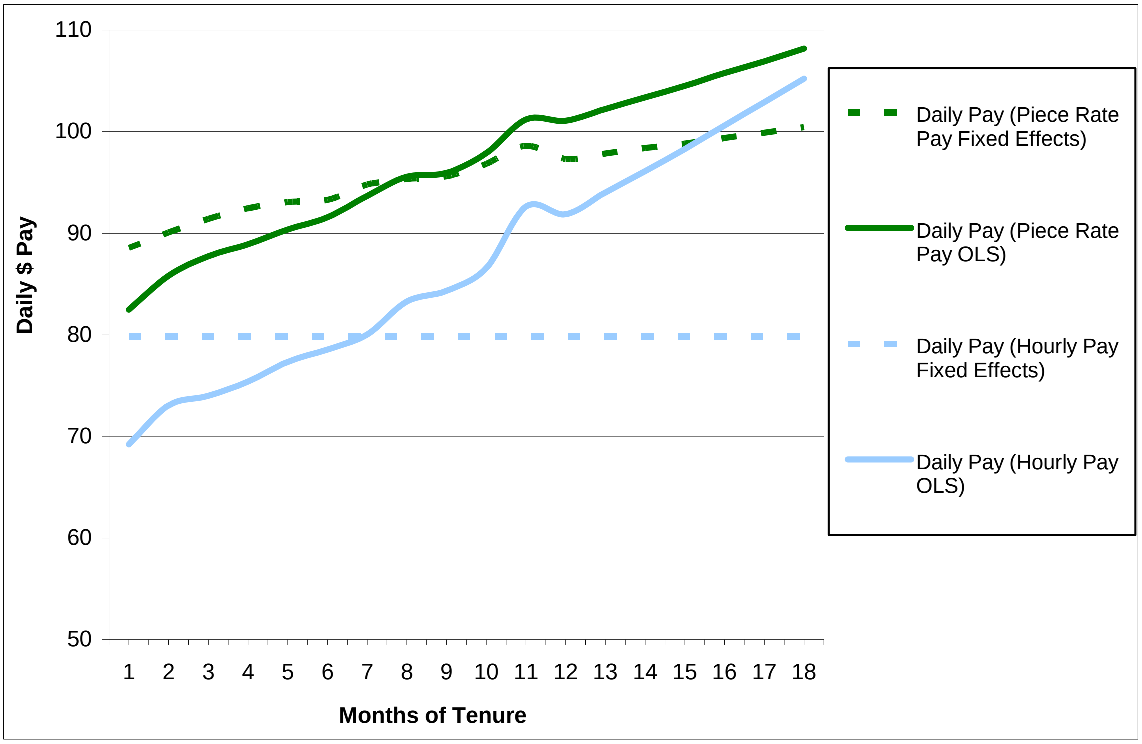

Figure 2: Predicted Pay-Tenure Profiles for New Hires (based on Table 1)

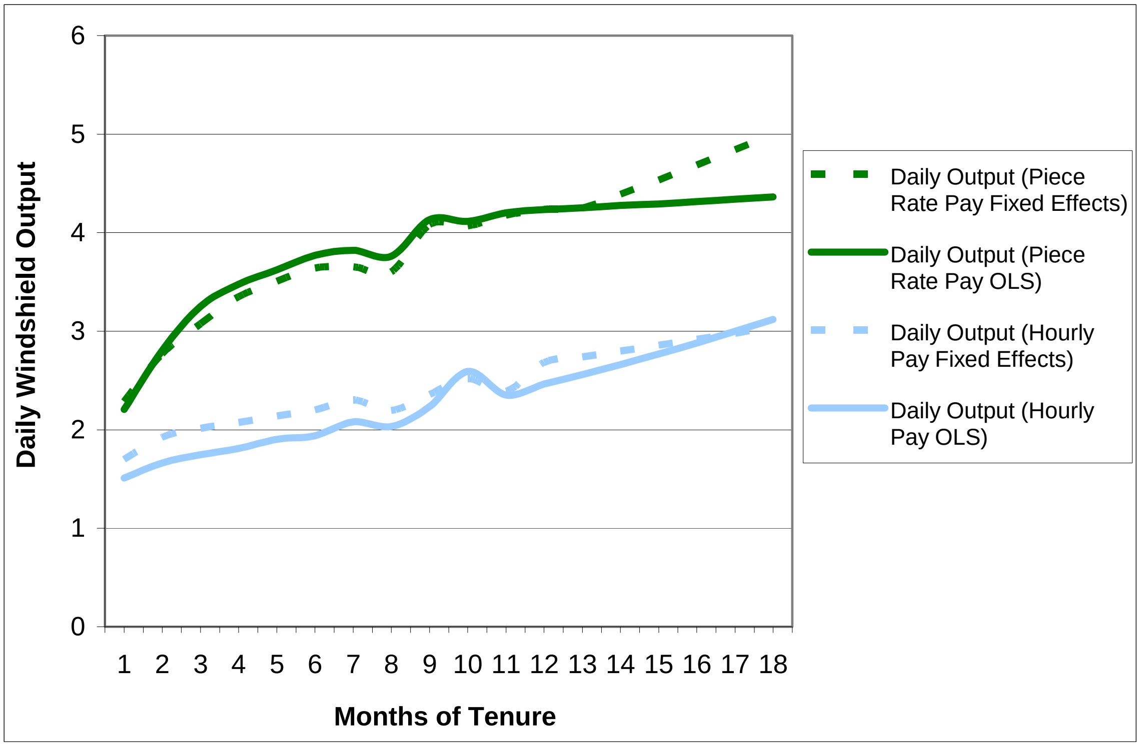

Figure 3: Predicted Output-Tenure Profiles for New Hires (based on Table 1)

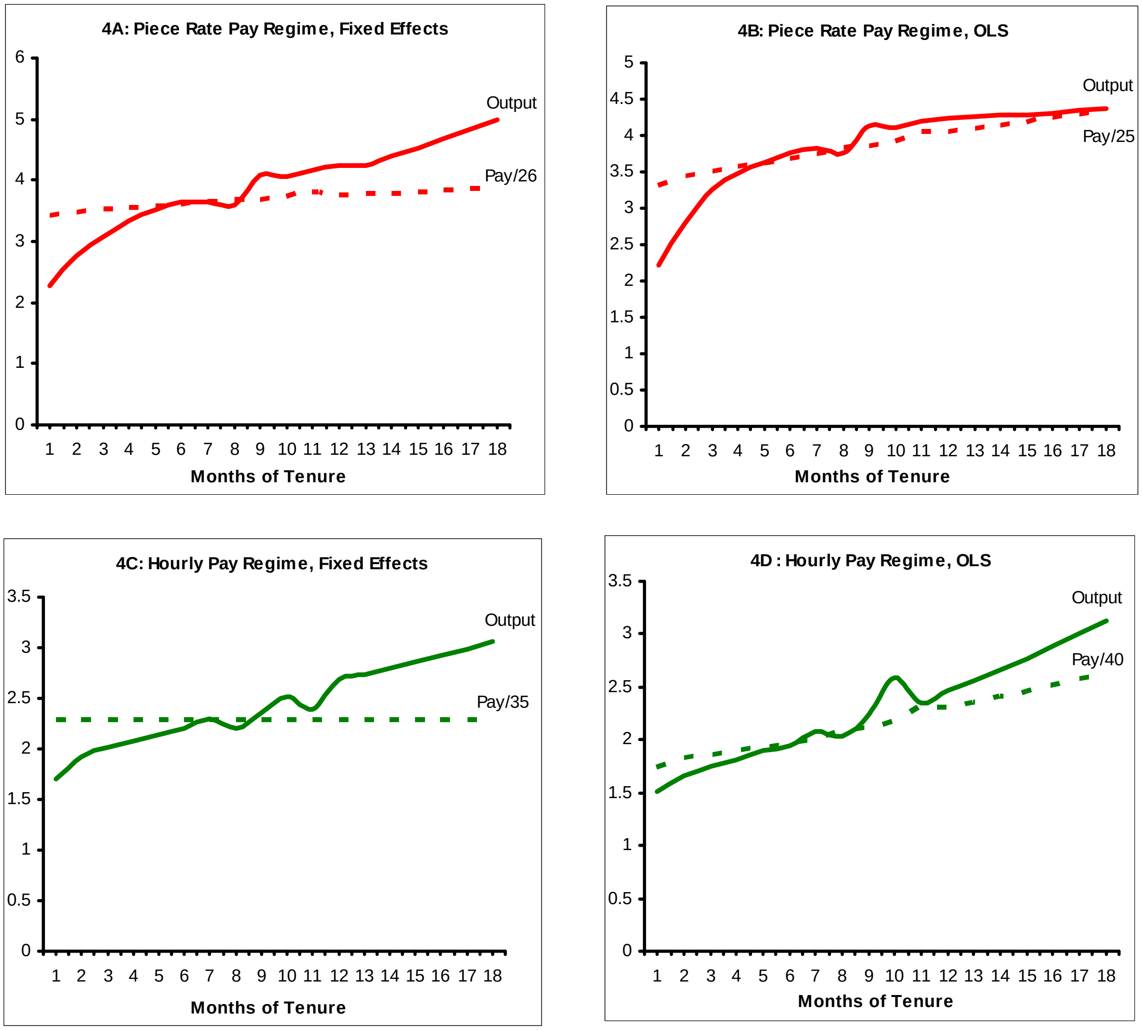

Figure 4: Comparing Predicted Output and Pay Profiles for New Hires (based on Table 1)

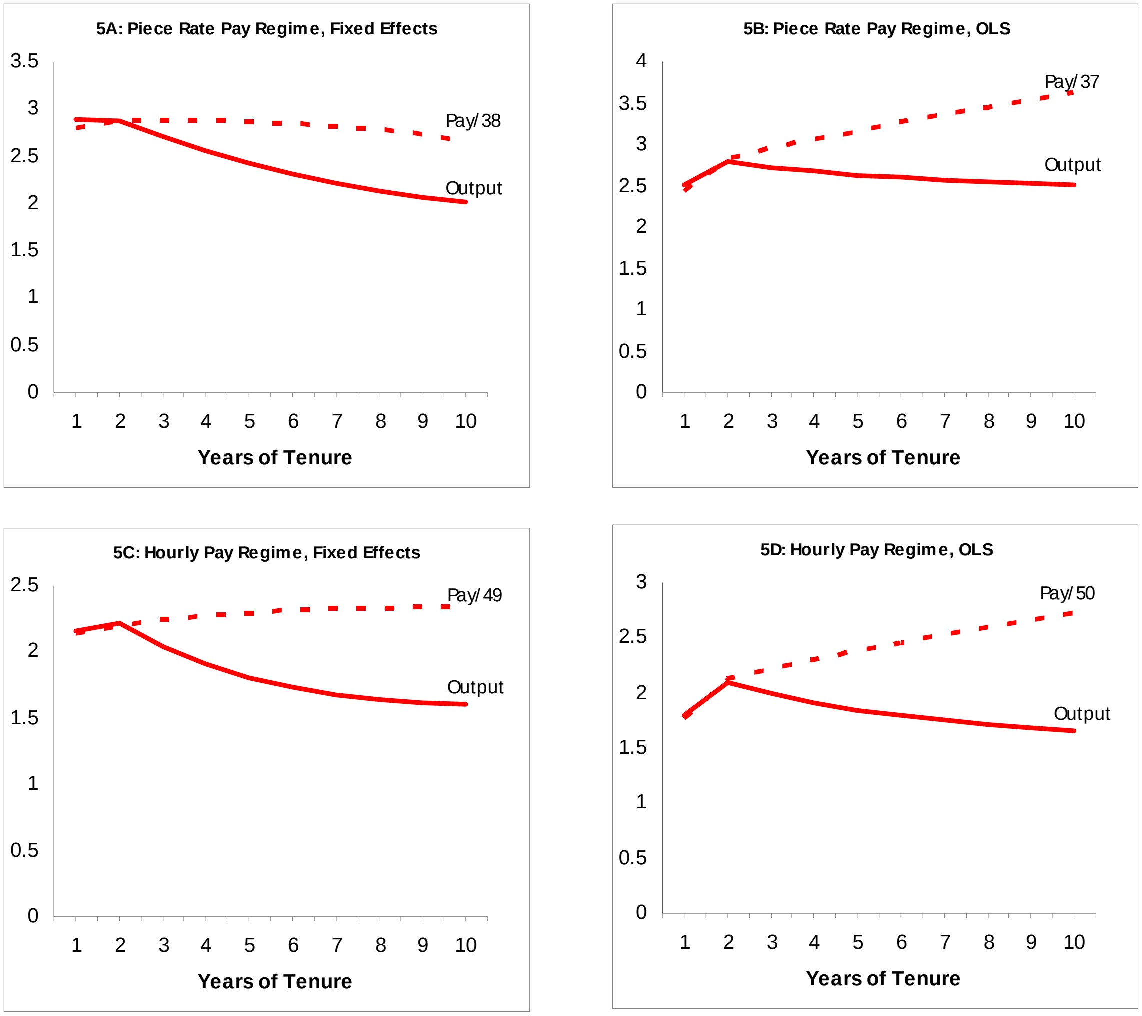

Figure 5: Comparing Predicted Output and Pay Profiles for Workers of All Ages (based on Table 2)

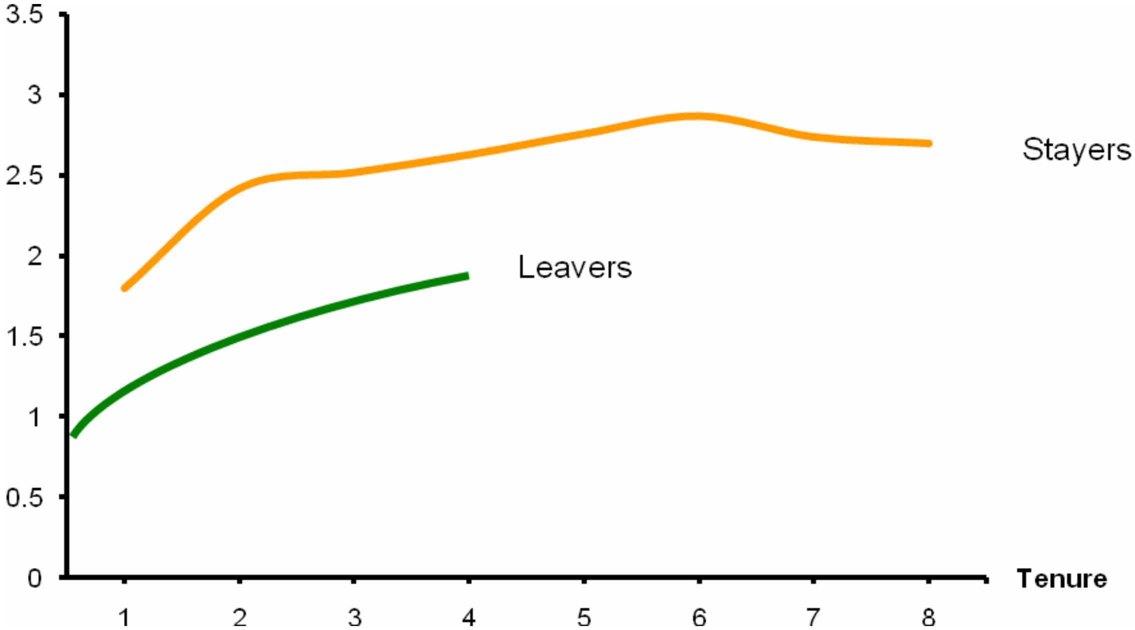

Figure 6: Predicted Output for Stayers Versus Leavers (Hourly Pay Plan)

Table 1

		ln(Daily Pay) Regressions				ln(Output) Regressions			
		Currently Paid Hourly Pay		Currently Paid Piece Rate Pay		Currently Paid Hourly Pay		Currently Paid Piece Rate Pay	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		FE	OLS	FE	OLS	FE	OLS	FE	OLS
Tenure dummies for those hired under hourly pay.*	tenure1 = 1	0.056	-0.570	(dropped)	(dropped)	-0.964	-1.580	(dropped)	(dropped)
		(0.66)	(-11.43)	(dropped)	(dropped)	(-2.66)	(-11.40)	(dropped)	(dropped)
	tenure2 = 1	0.109	-0.477	-0.120	-0.278	-0.667	-1.182	-0.624	-0.626
		(1.36)	(-9.53)	(-3.96)	(-11.71)	(-1.97)	(-8.50)	(-7.54)	(-9.39)
	tenure3 = 1	0.094	-0.456	-0.098	-0.248	-0.579	-1.029	-0.374	-0.276
		(1.27)	(-8.98)	(-3.65)	(-13.88)	(-1.85)	(-7.30)	(-5.13)	(-5.52)
	tenure4 = 1	0.079	-0.426	-0.087	-0.244	-0.529	-0.933	-0.219	-0.185
		(1.14)	(-8.25)	(-3.61)	(-15.62)	(-1.82)	(-6.50)	(-3.32)	(-4.22)
	tenure5 = 1	0.073	-0.388	-0.076	-0.218	-0.477	-0.808	-0.160	-0.153
		(1.15)	(-7.37)	(-3.46)	(-14.66)	(-1.78)	(-5.53)	(-2.67)	(-3.68)
	tenure6 = 1	0.059	-0.365	-0.071	-0.201	-0.432	-0.768	-0.117	-0.114
		(1.02)	(-6.74)	(-3.58)	(-14.10)	(-1.76)	(-5.11)	(-2.17)	(-2.84)
	tenure7 = 1	0.031	-0.338	-0.055	-0.172	-0.363	-0.622	-0.088	-0.069
		(0.60)	(-5.97)	(-3.09)	(-12.11)	(-1.62)	(-3.95)	(-1.81)	(-1.72)
	tenure8 = 1	0.035	-0.283	-0.048	-0.157	-0.431	-0.666	-0.102	-0.100
		(0.72)	(-4.73)	(-3.05)	(-11.07)	(-2.13)	(-4.01)	(-2.36)	(-2.51)
	tenure9 = 1	0.027	-0.266	-0.054	-0.140	-0.323	-0.487	-0.058	-0.051
		(0.61)	(-4.13)	(-3.80)	(-9.73)	(-1.75)	(-2.72)	(-1.50)	(-1.26)
	tenure10 = 1	-0.007	-0.232	-0.041	-0.117	-0.234	-0.258	-0.061	-0.055
		(-0.16)	(-3.21)	(-3.22)	(-8.03)	(-1.35)	(-1.28)	(-1.78)	(-1.36)
	tenure11 = 1	0.041	-0.147	-0.022	-0.079	-0.299	-0.384	-0.034	-0.034
		(1.04)	(-1.81)	(-1.98)	(-5.40)	(-1.80)	(-1.70)	(-1.12)	(-0.82)
	tenure12 = 1	0.029	-0.157	-0.035	-0.081	-0.148	-0.318	-0.019	-0.026
		(0.79)	(-1.83)	(-3.48)	(-5.34)	(-0.95)	(-1.33)	(-0.69)	(-0.61)
Tenure dummies for those hired under piece rate pay.**	tenure1 = 1			-0.076	-0.234			-0.478	-0.762
				(-3.31)	(-18.20)			(-7.62)	(-21.16)
	tenure2 = 1			-0.058	-0.184			-0.184	-0.305
				(-2.75)	(-13.69)			(-3.18)	(-8.10)
	tenure3 = 1			-0.052	-0.159			-0.142	-0.246
				(-2.69)	(-11.24)			(-2.66)	(-6.20)
	tenure4 = 1			-0.037	-0.122			-0.101	-0.170
				(-2.04)	(-7.86)			(-2.05)	(-3.90)
	tenure5 = 1			-0.036	-0.113			-0.053	-0.084
				(-2.13)	(-6.79)			(-1.15)	(-1.80)
	tenure6 = 1			-0.039	-0.099			-0.013	-0.029
				(-2.45)	(-5.50)			(-0.30)	(-0.57)
	tenure7 = 1			-0.020	-0.076			-0.060	-0.071
				(-1.26)	(-3.72)			(-1.41)	(-1.25)
	tenure8 = 1			-0.014	-0.040			-0.076	-0.058
				(-0.90)	(-1.75)			(-1.76)	(-0.90)
	_constant	4.382	4.735	4.542	4.652	1.115	1.510	1.073	1.105
		(92.25)	(80.8)	(258.34)	(352.85)	(5.56)	(9.27)	(22.36)	(29.91)
	Number of obs	2711	2711	5816	5816	2709	2709	5808	5808
	Adj R-squared	0.882	0.114	0.734	0.142	0.752	0.198	0.740	0.115

t-statistics in parentheses.

Regression also contains month and year dummies.

*In columns 1 and 2, and 5 and 6, the tenure dummies are months of tenure for the sample currently working under the old hourly pay regime and currently paid hourly pay. In columns 3 and 4, and 7 and 8, the dummies are months of tenure for those hired under houly pay but currently working under the piece rate pay. **These are tenure dummies for those hired under the piece rate pay and currently working under piece rate.

This table estimates regressions based on subsamples of new hires given based on their current pay regime in each column

	Table 2: Regressions for All Workers									
	ln(daily output)					ln(daily pay)				
	Hourly Pay		Piece Rate Pay			Hourly Pay		Piece Rate Pay		
	FE	OLS	FE	FE	OLS	FE	OLS	FE	FE	OLS
	(1)	(2)		(3)	(4)	(5)	(6)		(7)	(8)
Tenure first year	-0.124	-0.215	-0.063	-0.050	-0.136	-0.008	-0.131	-0.025	-0.025	-0.103
	(-3.61)	(-7.64)	(-3.33)	(-2.15)	(-6.99)	(-0.72)	(-15.98)	(-3.02)	(-2.50)	(-14.71)
Tenure	-0.124	-0.077	-0.075	-0.053	-0.037	0.031	0.055	0.010	0.010	0.055
	(-3.52)	(-6.35)	(-4.36)	(-1.96)	(-4.00)	(2.72)	(15.70)	(1.31)	(0.83)	(16.59)
$Tenure^2$	0.009	0.006	0.003	-0.001	0.003	-0.003	-0.003	-0.0016	-0.002	-0.003
	(2.46)	(5.44)	(2.28)	(-0.19)	(2.71)	(-2.78)	(-8.41)	(-3.31)	(-1.15)	(-9.95)
$Tenure^3$	-0.0002	-0.0002		0.0001	-0.0001	0.0001	0.0001		0.0000	0.0001
	(-2.10)	(-5.59)		(1.05)	(-2.80)	(2.98)	(6.27)		(-0.01)	(7.58)
Constant	1.010	0.873	1.198	1.162	1.089	4.629	4.564	4.678	4.678	4.548
	(10.32)	(13.82)	(22.29)	(9.94)	(35.41)	(146.47)	(248.07)	(197.3)	(166.88)	(407.60)
R^2	0.7927	0.0299	0.7660	0.7658	0.0175	0.8181	0.3075	0.7320	0.7318	0.2398
N	12839	12839	16573	16573	16573	12389	12389	16573	16573	16573

These regressions use the entire sample of both new hires and older workers, and the regression in each column is the subsample based on the pay regime under which each person is currently working.

t-statistics in parentheses. Tenure is years of tenure; $Tenure^2$ and $Tenure^3$ are the squared and cubed terms. The first row is a dummy variable for first year of tenure with the firm.

Table 3: ln(output) Regressions with separate "Leaver" Coefficients for Exiting Workers (New Hires only)

	Regression 1 - Fixed Effects				Regression 2 - OLS			
	Hired Under Hourly Pay		Hired Under Piece Rate Pay		Hired Under Hourly Pay		Hired Under Piece Rate Pay	
	Everyone	Leavers	Everyone	Leavers	Everyone	Leavers	Everyone	Leavers
PieceRatePay = 1	0.157	0.076			0.109	-0.128		
	(6.77)	(1.04)			(3.80)	(-1.41)		
tenure1 = 1	-0.535	0.260	-0.424	0.211	-0.944	-0.368	-0.552	-0.720
	(-7.72)	(2.71)	(-8.10)	(2.30)	(-15.30)	(-7.69)	(-7.81)	(-10.17)
tenure2 = 1	-0.269	0.188	-0.149	0.202	-0.646	-0.299	-0.262	-0.355
	(-4.15)	(2.02)	(-3.03)	(2.20)	(-10.55)	(-5.58)	(-3.73)	(-4.38)
tenure3 = 1	-0.157	0.111	-0.064	0.075	-0.504	-0.201	-0.162	-0.420
	(-2.62)	(1.23)	(-1.39)	(0.79)	(-8.26)	(-3.07)	(-2.33)	(-4.44)
tenure4 = 1	-0.082	0.079	-0.040		-0.397	-0.239	-0.185	
	(-1.49)	(0.89)	(-0.94)		(-6.48)	(-2.90)	(-2.77)	
tenure5 = 1	-0.050		0.012		-0.330	-0.228	-0.053	
	(-0.98)		(0.30)		(-5.38)	(-1.91)	(-0.78)	
tenure6 = 1	-0.031		0.036		-0.302		(dropped)	
	(-0.67)		(0.90)		(-4.90)		(dropped)	
tenure7 = 1	0.003				-0.226			
	(0.07)				(-3.60)			
tenure8 = 1	-0.044				-0.247			
	(-1.10)				(-3.88)			
tenure9 = 1	-0.016				-0.184			
	(-0.42)				(-2.85)			
tenure10 = 1	-0.029				-0.165			
	(-0.84)				(-2.52)			
tenure11 = 1	-0.019				-0.098			
	(-0.62)				(-2.23)			
tenure12 = 1	-0.008				-0.117			
	(-0.28)				(-1.75)			
Number of obs	8048				8048			
Adj R-squared	0.689				0.201			

These two regressions are for the subsample of all workers newly hired by the firm.
t-statistics in parentheses.
Regression also contains month and year dummies. Dependent variable is ln(daily output).
The tenure dummies are months of tenure. A "leaver" is a worker who stays less than 6 months: the columns labeled "leavers" are introducing four additional dummy variables for the tenure of leavers, so leavers full tenure effect is the sum of the coefficients for "everyone" and leavers. Regressions also contain six dummy variables for shifts in the return to tenure after piece rate pay for stages: None are significant.

Table 4: ln(daily pay) Regressions with separate "Leaver" Cofficients for Exiting Workers (New Hires only)

	Regression 1 - Fixed Effects				Regression 2 - OLS			
	Hired Under Hourly Pay		Hired Under Piece Rate Pay		Hired Under Hourly Pay		Hired Under Piece Rate Pay	
	Everyone	Leavers	Everyone	Leavers	Everyone	Leavers	Everyone	Leavers
PieceRatePay = 1	0.069	-0.025			0.047	0.036		
	(9.32)	(-1.06)			(4.50)	(1.07)		
tenure1 = 1	-0.160	0.022	-0.091	0.041	-0.344	-0.062	-0.128	-0.081
	(-7.19)	(0.73)	(-5.40)	(1.39)	(-15.21)	(-3.54)	(-4.94)	(-3.12)
tenure2 = 1	-0.101	0.032	-0.052	0.015	-0.265	-0.033	-0.081	-0.062
	(-4.87)	(1.08)	(-3.33)	(0.50)	(-11.83)	(-1.67)	(-3.14)	(-2.11)
tenure3 = 1	-0.098	0.019	-0.038	-0.014	-0.244	-0.051	-0.051	-0.063
	(-5.10)	(0.66)	(-2.58)	(-0.46)	(-10.89)	(-2.11)	(-1.99)	(-1.81)
tenure4 = 1	-0.099	0.033	-0.029		-0.225	-0.068	-0.034	
	(-5.60)	(1.16)	(-2.13)		(-10.04)	(-2.26)	(-1.40)	
tenure5 = 1	-0.087	(dropped)	-0.032		-0.195	-0.085	-0.024	
	(-5.29)	(dropped)	(-2.44)		(-8.66)	(-1.94)	(-0.96)	
tenure6 = 1	-0.085		-0.030		-0.175		(dropped)	
	(-5.71)		(-2.38)		(-7.74)		(dropped)	
tenure7 = 1	-0.077				-0.148			
	(-5.58)				(-6.44)			
tenure8 = 1	-0.065				-0.124			
	(-5.07)				(-5.32)			
tenure9 = 1	-0.067				-0.106			
	(-5.70)				(-4.48)			
tenure10 = 1	-0.056				-0.082			
	(-5.18)				(-3.45)			
tenure11 = 1	-0.032				-0.087			
	(-3.15)				(-5.39)			
tenure12 = 1	-0.038				-0.034			
	(-3.93)				(-1.40)			
Number of obs	8048				8048			
Adj R-squared	0.689				0.227			

These two regressions are for the subsample of all workers newly hired by the firm.
t-statistics in parentheses.
Regression also contains month and year dummies. Dependent variable is ln(daily output).
The tenure dummies are months of tenure. A "leaver" is a worker who stays less than 6 months: the columns labeled "leavers" are introducing four additional dummy variables for the tenure of leavers, so leavers full tenure effect is the sum of the coefficients for "everyone" and leavers. Regressions also contain six dummy variables for shifts in the return to tenure after piece rate pay for stages: None are significant.

Appendix Table A1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
output	2.888	1.396	0.010	14.580
ln(output)	0.895	0.696	-4.605	2.680
daily pay	89.288	25.722	11.500	866.187
ln(daily pay)	4.458	0.255	2.442	6.764
hired with piece rate	0.246	0.430	0.000	1.000
switch to piece rate	0.436	0.496	0.000	1.000
tenure1=1 dummy	0.139	0.346	0.000	1.000
tenure2=1	0.123	0.328	0.000	1.000
tenure3=1	0.108	0.310	0.000	1.000
tenure4=1	0.094	0.292	0.000	1.000
tenure5=1	0.083	0.276	0.000	1.000
tenure6=1	0.074	0.262	0.000	1.000
tenure7=1	0.063	0.243	0.000	1.000
tenure8=1	0.056	0.229	0.000	1.000
tenure9=1	0.049	0.216	0.000	1.000
tenure10=1	0.043	0.203	0.000	1.000
tenure11=1	0.038	0.192	0.000	1.000
tenure12=1	0.034	0.180	0.000	1.000
tenure1=1 for hired under piece rate	0.049	0.216	0.000	1.000
tenure2=1 for hired under piece rate	0.041	0.199	0.000	1.000
tenure3=1 for hired under piece rate	0.035	0.183	0.000	1.000
tenure4=1 for hired under piece rate	0.027	0.163	0.000	1.000
tenure5=1 for hired under piece rate	0.023	0.149	0.000	1.000
tenure6=1 for hired under piece rate	0.019	0.135	0.000	1.000
tenure7=1 for hired under piece rate	0.014	0.117	0.000	1.000
tenure8=1 for hired under piece rate	0.011	0.102	0.000	1.000
leaver with less than 6 months final tenure	0.128	0.334	0.000	1.000
tenure1=1 for hired under hourly pay plan	0.090	0.286	0.000	1.000
tenure2=1 for hired under hourly pay plan	0.082	0.274	0.000	1.000
tenure3=1 for hired under hourly pay plan	0.073	0.260	0.000	1.000
tenure4=1 for hired under hourly pay plan	0.067	0.249	0.000	1.000
tenure5=1 for hired under hourly pay plan	0.060	0.238	0.000	1.000
tenure6=1 for hired under hourly pay plan	0.055	0.229	0.000	1.000
tenure7=1 for hired under hourly pay plan	0.049	0.216	0.000	1.000
tenure8=1 for hired under hourly pay plan	0.045	0.207	0.000	1.000
tenure9=1 for hired under hourly pay plan	0.040	0.197	0.000	1.000
tenure10=1 for hired under hourly pay plan	0.037	0.188	0.000	1.000
tenure11=1 for hired under hourly pay plan	0.034	0.181	0.000	1.000
tenure12=1 for hired under hourly pay plan	0.030	0.172	0.000	1.000

Appendix Table A2: Fixed Effects ln(output) Regressions		
	Regression 1	
	Hired Under Hourly Pay	Hired Under Piece Rate Pay
PieceRatePay = 1	0.185	
	(8.40)	
tenure1 = 1	-0.547	-0.435
	(-7.88)	(-8.83)
tenure2 = 1	-0.278	-0.138
	(-4.31)	(-3.01)
tenure3 = 1	-0.166	-0.095
	(-2.77)	(-2.20)
tenure4 = 1	-0.094	-0.053
	(-1.69)	(-1.28)
tenure5 = 1	-0.063	-0.007
	(-1.23)	(-0.17)
tenure6 = 1	-0.049	0.028
	(-1.03)	(0.71)
tenure7 = 1	-0.013	
	(-0.29)	
tenure8 = 1	-0.057	
	(-1.42)	
tenure9 = 1	-0.025	
	(-0.68)	
tenure10 = 1	-0.037	
	(-1.09)	
tenure11 = 1	-0.026	
	(-0.79)	
tenure12 = 1	-0.012	
	(-0.39)	
Constant	0.841	
	(6.80)	
Number of obs	8527	
Adj R-squared	0.685	

This is one regression using the subsample of all new hires only, and permits the tenure profile to differ for those hired under hourly pay (Column 1) versus hired under piece rate pay (Column 2).
Regression also contains month and year dummies.
t-statistics in parentheses.
Dependent variable is ln(daily output).
In column 1, the tenure dummies are months of tenure for the sample hired under the old hourly pay regime; in column 2 the dummies are months of tenure hired under the piece rate pay.
Column 1 also contains six dummy variables for shifts in the returns to tenure after piece rate pay: none are significant