Employer Learning, Job Changes, and Wage Dynamics*

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Abstract

This paper takes a new approach to testing whether employer learning is public or private. We show that public and private learning schemes make two distinct predictions about the curvature of the wage growth path when a worker changes jobs, since less information about the worker's productivity is transferred to a new employer in the private learning case than in the public learning case. This prediction enables us to account for individual and job-match heterogeneity, which was not possible in previous tests. Using the NLSY79, we find that employer learning is public for high-school graduates and private for college graduates.

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1 Introduction

When young workers enter the labor market, their productivity is generally unknown, and employers use easily observable measures of human capital, such as education, to evaluate these workers. Over the course of workers' careers, information about their productivity is gradually revealed and updated by employers. Wages then become more dependent on actual productivity and less dependent on easily observable measures of human capital. This hypothesis of employer learning has been empirically tested, and the results have been consistent with the hypothesis. In particular, Farber and Gibbons (1996) and Altonji and Pierret (2001) argue that in the presence of such employer learning, the contribution to wages of factors observed by researchers but not employers (e.g., test scores) increases with workers' experience, while the contribution to wages of factors observed by both employers and researchers (e.g., education) decreases with workers' experience.

A common assumption, made by Farber and Gibbons (1996) and Altonji and Pierret (2001), among others, is that all employers in the market obtain the same amount of information about the productivity of workers. In other words, it is assumed that information gathered by incumbent employers about workers' productivity is fully transmitted to outside employers. If this assumption holds, employer learning is public. However, if information is asymmetric among employers, learning is private.

Whether learning is public or private has been empirically tested in various ways. For example, Schönberg (2007) develops a test based on a learning model with voluntary job changes, and Pinkston (2009) considers a labor market in which incumbent and outside employers compete with each other by offering wages according to an ascending auction rule. Interestingly, these two theoretical approaches result in a similar empirical strategy. According to Schönberg (2007), if incumbent employers learn more than outside employers about workers' productivity, the contribution to wages of factors observed by researchers but not employers (e.g., test scores) will increase with job tenure (or, according to Pinkston (2009), over a spell of continuous employment), while the contribution to wages of factors observed by both employers and researchers (e.g., education) will decrease with job tenure (or, again, over a spell of continuous employment).[1] If learning is public, a similar logic holds with respect to

[1] Applying the second-price sealed-bid auction theory, Pinkston (2009) shows that an employer's private learning is reflected in a worker's wage and is then transmitted to the next employer when the worker makes a job-to-job transition. In such a case, the wage becomes more dependent on the worker's test scores as the spell of the worker's continuous employment increases, rather than as the worker's tenure increases.

experience rather than job tenure (or length of the employment spell).

This paper reinvestigates whether employer learning is public or private, with an emphasis on the empirical tests of wage equations. We have two reasons for employing this approach. First, the empirical evidence points in different directions. For example, Schönberg's evidence supports the public learning hypothesis for high-school graduates, whereas Pinkston's evidence supports the private learning hypothesis. Second, our test utilizes theoretical predictions on the curvature of the wage growth path. Most tests of learning rely on coefficient estimates of experience and tenure (or length of the employment spell) in a wage-level equation.[2] However, the literature on returns to seniority suggests that the ordinary least squares (OLS) estimates are inconsistent due to fixed unobserved individual-specific and job-match-specific components. A strategy that is widely used to deal with this problem is first-differencing. However, this strategy is not applicable to existing tests because the coefficients for experience and tenure are not separately identified. Our test statistics are identified under first-differencing, since the proposed test exploits the implications of the theory of the speed of learning. Although it is possible to use an instrumental variables (IV) approach in a wage-level model, as in Pinkston (2009), our test provides additional evidence of the type of employer learning.

The main objective of this paper is to develop a new test for identifying the type of employer learning that is consistent with the theoretical predictions regarding the speed of employer learning. We let the employer form expectations about the productivity of workers based on available information, and update his or her beliefs in response to new information being revealed. In the case of public learning, the wage growth rate in the new job will be a continuation of the wage growth rate in the previous job, although the path continuity may be broken by the job change.[3] This implies that the contribution to wages of factors observed only by researchers will increase at a decreasing rate with experience but not with

[2] There are other approaches that test for the type of employer learning. Gibbons and Katz (1991) find empirical support for an asymmetric-information model of layoffs. In their model, layoffs signal that workers are of low ability. If one assumes that job losses due to plant closings do not send such a negative signal, then post-displacement wages should be lower for workers who are laid off than for workers displaced by plant closings. The results, based on the CPS data, support the model's predictions. Using many more years of the CPS data, Hu and Taber (2011) find that this lemon effect of layoffs holds only for white males. More recently, Kahn (2013) derives a learning model with endogenous mobility and asymmetric information that nests symmetric learning as a special case. She tests the model using the NLSY79 and finds support for asymmetric learning. Specifically, she finds that in one period, outside firms reduce expectation errors by roughly a third of the incumbent's reduction.

[3] Since references to a specific job imply references to a specific employer, we use the terms *job* and *employer* interchangeably here.

tenure. In the case of private learning, the wage growth path in the new job will be as steep as that in the first job at the time of labor market entry. This implies that the contribution to wages of factors observed only by researchers will increase at a decreasing rate with tenure but not with experience. Because our testing implications utilize the change in the speed of learning, the test statistic can be consistently estimated from a first-differenced wage equation for individuals who stay in the same job for two adjacent periods.

Using the sample drawn from the National Longitudinal Survey of Youth 1979 (NLSY79), we find that for high-school graduates, the contribution to wages of factors observed only by researchers increases at a decreasing rate with experience but not with tenure. This implies that the amount of information that potential employers have about worker ability does not differ from the amount of information that incumbent employers have. Therefore, learning is public for high-school graduates. In contrast, for college graduates, we find that the contribution to wages of factors observed only by researchers increases at a decreasing rate with tenure but not with experience. Therefore, learning is private for college graduates. We also find differential learning patterns, depending on the reasons for job changes. Specifically, for college graduates, the signs are consistent with the private employer learning for those whose new jobs started due to displacement from previous jobs by plant closings, although the results for those who are displaced by layoffs are inconclusive. Our results are consistent with Gibbons and Katz's (1991) finding that workers who are displaced by plant closing do not convey negative signals to outside employers.

The paper proceeds as follows. Section 2 develops our theoretical framework and identifies its testable implications. In Section 3, the data are introduced. Section 4 presents our empirical specification and discusses our main findings. Section 5 verifies the robustness of the findings. Section 6 offers our conclusions.

2 Information and Employer Learning

2.1 Employer Predictions regarding Worker Productivity

Consider an individual i who works with an employer j and has t years of labor market experience. Let p_{ijt} be the log of productivity of worker i in job j in year t in the labor market:

$$p_{ijt} = f\left(H_{ijt}\right) + \omega_{ij} + \eta_i, \tag{1}$$

where f is a known function, H_{ijt} consists of easily observable measures of human capital (including education, experience, and job tenure), ω_{ij} involves elements that are observed by employers but unknown to researchers, and η_i consists of other factors that affect productivity but are not observed directly by employers.

We make several assumptions regarding the fixed unobserved heterogeneity, ω_{ij} and η_i, in Equation (1). First, ω_{ij} consists of individual-specific and job-match-specific components that are observed by employers but not researchers. We assume that each employer has his or her own prior belief about the productivity of applicants upon learning easily observable factors such as which school applicants attended, what their major was, which courses they have taken, and what grade point average they attained. In general, ω_{ij} is nonzero because employer j uses public as well as private information to evaluate the productivity of worker i. We assume that the value of ω_{ij} is revealed to the employer at the beginning of an employment relationship but is unknown to the researcher. This value is time-invariant within an employment relationship and is different for outside employers, since they offer different tasks and have different information sets. Second, employers cannot directly observe η_i and they must learn about it. We assume that η_i is a normal random variable with expectation zero and variance σ_η^2, and that this distributional assumption is common to all employers. Although η_i is unobservable to employers, researchers who have access to data may have partial information about η_i. Examples of η_i are innate ability and test scores. Workers may possess different η_i even if they are observationally equivalent on the employer's initial information set and therefore have identical ω_{ij}.[4]

When employer j receives applications, he or she must make predictions about the unknown η_i. These predictions, however, involve errors, as applicants send noisy signals of their productivity to potential employers. Let $\overrightarrow{s}_{ij}$ denote the private signals that employer j receives from applicant i about η_i before j makes a new job offer to i, but it does not include H_{ijt}, ω_{ij}, and past performance records. We then have

$$\overrightarrow{s}_{ij} = \eta_i + \xi_{ij}, \tag{2}$$

where ξ_{ij} is a normal random variable that is independent of η_i and that has expectation zero and variance σ_ξ^2. Examples of $\overrightarrow{s}_{ij}$ include private signals such as judgements about produc-

[4]Studies of employer learning, including Schönberg (2007), Pinkston (2009), and Kahn (2013), are all concerned about testing whether learning about η_i is public or private. In contrast, Jovanovic (1979) constructs a model in which employers learn about job match quality over the worker's job tenure. In the robustness section (Section 5), we test whether learning about job match quality is more important than learning about η_i.

tivity and personality based on what is revealed in reference letters or during an interview. If applicant i has labor market experience, $\overrightarrow{s}_{ij}$ also includes the latest wage offered by an incumbent employer and information about whether the job change was due to a quit of a layoff.

Consider an individual i who completes his or her schooling and enters the labor market for the first time.[5] Employer j makes a prediction about worker i's productivity using all available information: H_{ij1}, ω_{ij}, and $\overrightarrow{s}_{ij}$. Employer j's expected log productivity for worker i at the time of labor market entry, EP_{ij1}, will be given by

$$\begin{aligned} EP_{ij1} &= E\left[p_{ij1}|H_{ij1}, \omega_{ij}, \overrightarrow{s}_{ij}\right] \\ &= f\left(H_{ij1}\right) + \omega_{ij} + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\xi^2}\overrightarrow{s}_{ij}, \end{aligned} \tag{3}$$

where the second equation is derived using the property of multivariate normal distribution.

Once worker i and employer j are matched, worker i will start producing output in each period t. The realized log output, $\widetilde{q}_{ijt}$, is a proxy for the worker's true log productivity, given in Equation (1). Define q_{ijt} as the stochastic part of $\widetilde{q}_{ijt}$ from employer j's point of view:

$$\begin{aligned} q_{ijt} &= \widetilde{q}_{ijt} - f\left(H_{ijt}\right) - \omega_{ij} \\ &= \eta_i + \varepsilon_{ijt}, \end{aligned} \tag{4}$$

where ε_{ijt} is an *i.i.d.* normal random variable with expectation zero and variance σ_ε^2 and is independent of η_i and ξ_{ij}. In each period, employer j acquires new information, q_{ijt}, by observing the realized output in the previous period. In this way, employer j updates his or her initial evaluation of the productivity of worker i beyond the signal $\overrightarrow{s}_{ij}$. Then, employer j's expectation of the log productivity of worker i in t years of experience or tenure is determined by

$$\begin{aligned} EP_{ijt} &= E\left[p_{ijt}|H_{ijt}, \omega_{ij}, \overrightarrow{s}_{ij}, q_{ij1}, ..., q_{ij,t-1}\right] \\ &= f\left(H_{ijt}\right) + \omega_{ij} + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \frac{\sigma_\varepsilon^2\sigma_\xi^2}{\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2}} \left(\frac{\sigma_\varepsilon^2\overrightarrow{s}_{ij} + \sigma_\xi^2\sum_{\tau=1}^{t-1} q_{ij\tau}}{\sigma_\varepsilon^2 + (t-1)\,\sigma_\xi^2}\right). \end{aligned} \tag{5}$$

In Equation (5), experience and tenure are identical because we assume that this is worker i's first job. The final term in the second equation in Equation (5) has important implications. First, as worker i becomes more experienced, employer j learns more about η_i. This is because

[5] Both potential experience and tenure are equal to one during the worker's first year in the labor market.

the first and second factors of the final term converge to unity and η_i, respectively, as $t \to \infty$. Second, the amount of updated information decreases with t years of experience or tenure. In other words, the speed of convergence slows down. To demonstrate this, it is sufficient to show that the first factor of the final term is increasing in t at a decreasing rate, i.e.,

$$\frac{\partial}{\partial t} \frac{\sigma_\eta^2}{\sigma_\eta^2 + \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2}} > 0 \text{ and } \frac{\partial^2}{\partial t^2} \frac{\sigma_\eta^2}{\sigma_\eta^2 + \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2}} < 0, \tag{6}$$

which is also proved in Pinkston (2006).[6]

Now suppose that worker i changes to a new employer j' at experience $T+1$. Then, the tenure at the new job becomes one. The new employer j' may or may not observe worker i's past performance history, $\{q_{ij1}, ..., q_{ij,t-1}\}$. If past performance records are perfectly transferred to outside firms, then learning is public or symmetric. If not, learning is private or asymmetric. The signal $\overrightarrow{s}_{ij'}$ that the new employer j' receives from applicant i about η_i at the time of the job change may include worker i's last wage with the previous employer j, regardless of whether learning is symmetric or not.[7] The signal $\overrightarrow{s}_{ij'}$ may also include information about whether the job change was due to a quit or a layoff.

In the case of public learning, the expected log productivity at experience $T+1$ and tenure 1 will be determined by

$$\begin{aligned} EP_{ij',T+1} &= E\left[p_{ij',T+1} | H_{ij',T+1}, \omega_{ij'}, q_{ij1}, ..., q_{ijT}, \overrightarrow{s}_{ij'}\right] \\ &= f\left(H_{ij',T+1}\right) + \omega_{ij'} + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + T\sigma_\xi^2}} \left(\frac{\sigma_\varepsilon^2 \overrightarrow{s}_{ij'} + \sigma_\xi^2 \sum_{\tau=1}^{T} q_{ij\tau}}{\sigma_\varepsilon^2 + T\sigma_\xi^2} \right). \end{aligned} \tag{7}$$

As worker i continues to work with the new employer j', the worker's expected log productivity at experience $T+s$ and tenure s, $s \geq 2$, will be determined by

$$\begin{aligned} EP_{ij',T+s} &= E\left[p_{ij',T+s} | H_{ij',T+s}, \omega_{ij'}, q_{ij1}, ..., q_{ijT}, \overrightarrow{s}_{ij'}, q_{ij',T+1}, ..., q_{ij',T+s-1}\right] \\ &= f\left(H_{ij',T+s}\right) + \omega_{ij'} \\ &\quad + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + (T+s-1)\sigma_\xi^2}} \left(\frac{\sigma_\varepsilon^2 \overrightarrow{s}_{ij'} + \sigma_\xi^2 \left(\sum_{\tau=1}^{T} q_{ij\tau} + \sum_{\tau=T+1}^{T+s-1} q_{ij'\tau} \right)}{\sigma_\varepsilon^2 + (T+s-1)\sigma_\xi^2} \right). \end{aligned} \tag{8}$$

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[6] The above inequalities hold because $\frac{\partial}{\partial t} \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2} = -\frac{\sigma_\varepsilon^2 \sigma_\xi^4}{\left(\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2\right)^2} < 0$ and $\frac{\partial^2}{\partial t^2} \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2} = \frac{2\sigma_\varepsilon^2 \sigma_\xi^6}{\left(\sigma_\varepsilon^2 + (t-1)\sigma_\xi^2\right)^3} > 0$. Lange (2007) finds that the above inequalities hold empirically under the assumption of public learning.

[7] In our model, learning is public when the worker's entire performance record is transferred to the new employer. In contrast, learning is public in Pinkston (2009) when the last wage by the previous employer is transferred to the new employer.

On the other hand, in the case of private learning, past outcomes do not play a role in forming expectations at experience $T+1$ and tenure 1; the equation is thus

$$\begin{aligned} EP_{ij',T+1} &= E\left[p_{ij',T+1} | H_{ij',T+1}, \omega_{ij'}, \overrightarrow{s}_{ij'}\right] \\ &= f\left(H_{ij',T+1}\right) + \omega_{ij'} + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\xi^2} \overrightarrow{s}_{ij'}. \end{aligned} \tag{9}$$

In later periods, the expected log productivity at experience $T+s$ and tenure s, $s \geq 2$, is determined by

$$\begin{aligned} EP_{ij',T+s} &= E\left[p_{ij',T+s} | H_{ij',T+s}, \omega_{ij'}, \overrightarrow{s}_{ij'}, q_{ij',T+1}, ..., q_{ij',T+s-1}\right] \\ &= f\left(H_{ij',T+s}\right) + \omega_{ij'} + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \frac{\sigma_\varepsilon^2 \sigma_\xi^2}{\sigma_\varepsilon^2 + (s-1)\sigma_\xi^2}} \left(\frac{\sigma_\varepsilon^2 \overrightarrow{s}_{ij'} + \sigma_\xi^2 \sum_{\tau=T+1}^{T+s-1} q_{ij'\tau}}{\sigma_\varepsilon^2 + (s-1)\sigma_\xi^2} \right). \end{aligned} \tag{10}$$

The equations of expected log productivity that are shown in (7), (8), (9), and (10) imply that the amount of additional learning depends on *experience* in the case of public learning, and on *tenure* in the case of private learning. To see this point, suppose that there is a mass of workers with $\eta_i = \eta > 0$, and consider an average worker among them. Figure 1A describes the dynamics of the expected log productivity of the average worker under public and private learning schemes when there is a job change, where $f(H_{ijt})$ is set to zero for simplicity. Due to Condition (6), the shape of the expected log productivity paths will be concave with respect to either experience or tenure, depending on the type of employer learning. In the case of public learning, the shape of the expected log productivity path is concave for experience. Therefore, the overall slope of the path will not be affected by a job change, although the path continuity may be broken by the change in ω_{ij} (see the lines *EP, Public* in Figure 1A). In the case of private learning, however, the shape of the expected log productivity path is concave for tenure, and thus, the overall slope of the path for the new job will be the same as it is for the worker's first job after leaving school (see the lines *EP, Private* in Figure 1A).

Proposition 1. Suppose that a worker moves to a new job. If learning is public, past performance records will be available to the new employer, and the growth rate of the worker's expected log productivity in the new job will be a continuation of the corresponding growth rate in the previous job. If learning is private, past performance records will be unavailable to the new employer, and the growth rate of the worker's expected log productivity in the new job will be as steep as in the first job at the time of labor market entry.

It is important to note that this prediction holds even if job changes are endogenous. For example, quits and layoffs may send different messages to new employers by affecting $\overrightarrow{s}_{ij}$ and therefore causing a systematic correlation between $\overrightarrow{s}_{ij}$ and ω_{ij}. However, for any given $\overrightarrow{s}_{ij}$, the wage dynamics after a job change will be explained by (7), (8), (9), and (10). Although useful, the results in Proposition 1 are not directly applicable to a test of employer learning, since the expected log productivity is not available from the data. In the next subsection, we explore the relationship between expected log productivity and log wages in order to develop a feasible test of whether learning is public or private.

2.2 Relationship between Expected Productivity and Wages

Expected productivity and wages are closely related, but the relationship will vary depending on whether employer learning is public or private.[8] Let w_{ijt} be worker i's log wage in job j with t years of experience. In the case of public learning, the wage is equal to expected productivity. This is because all employers have the same amount of information about each worker and because any wage offer below the worker's expected productivity will be outbid by slightly higher wage offers. Therefore, the expected log productivity equations (3), (5), (7), and (8) are also the log wage equations.[9]

If learning is private, we can employ the logic developed in Pinkston (2009). In his setting, incumbent and outside employers compete with each other by offering wages according to an ascending auction rule. This framework is useful because the results of a second-price sealed-bid auction theory can be directly employed. In this wage-offer game, a dominant strategy is to make an offer that equals expected productivity; the winning employer is the employer who makes the highest wage offer, and the contract wage equals the second highest wage offer.[10] This strategy has the following implications. If the worker continues to work for the current employer, the contract log wage will not exceed the worker's log productivity as evaluated

[8] In this discussion, we follow the convention in this literature that all wage contracts are spot contracts and that long-term contracts are not possible. See Altonji and Pierret (2001) for the details of this logic.

[9] More precisely, the log wage equals the log expected productivity, which is different from the expected log productivity due to Jensen's inequality. However, it is known that this difference can be proxied by observable variables. See Altonji and Pierret (2001) for details.

[10] This logic holds regardless of whether ω_{ij} is included in the model. One necessary condition, however, is that the number of wage offers a worker receives in a year must be sufficiently large. While it is not possible to observe offer arrival rates, we may learn about the lower bound of arrival rates among unemployed workers from the duration of unemployment. Historically, the unemployment duration in the United States has not been long. In the Current Population Survey from 1981 to 2002, the average unemployment duration for men is 16.9 weeks, according to Mukoyama and Şahin (2009). Furthermore, among white men in our NLSY79 sample, 85.4 percent moved to new jobs within twelve months.

by the current employer. This contract wage, however, will function as a signal to new, competing employers in the next period. Therefore, the wage offer by new outside employers in the next period will at least equal the current contract wage plus a natural increase in wages due to human capital accumulation, $f(H_{ij',t+1}) - f(H_{ijt})$. If the worker decides to stay in his/her current job in the next period, the gap between the current employer's expectations regarding the worker's productivity and the contract wage will decline.

Next, for a worker who continues to work for the same employer, we show that the speed of convergence between the incumbent employer's expectation of the worker's productivity and realized wages slows down. This is a sufficient condition for increments in wage growth paths to decrease with job tenure, which is our key testing strategy. However, this result follows straightforwardly from Pinkston (2009). In our model, due to outside offers, the sequence of wages converges to the sequence of the incumbent employer's expectations regarding the worker's productivity. Because the increments of a converging sequence converge to zero, the speed of convergence decreases with job tenure.

A job change implies that at least one wage offer made by an outside employer exceeds the current employer's wage offer. In this case, the evaluation of the worker's productivity by the employer with the second highest wage offer is transmitted to the winning employer, although the worker's entire performance history is not. After a job change, the wage growth path becomes steeper, due to Equations (9) and (10). If the number of outside employers does not vary over time or is very large, we can expect that the wage growth path in the new job will be the same as it is in the first job at the time of labor market entry, conditional on job tenure. If the number of outside employers changes over time, however, the wage growth rate in the new job will not necessarily be the same as it is in the first job because the expected value of the second highest wage offer will be a function of the number of participants. In any event, we derive the prediction that the wage growth path in the new job will be steeper in the case of private learning than the wage growth path in the new job in the case of public learning.

> **Proposition 2.** Suppose that a worker moves to a new job. If learning is public, the wage growth path in the new job will be a continuation of the wage growth path in the previous job. If learning is private, the wage growth path in the new job will be closer to that of the first job at the time of labor market entry.

The wage paths described in Proposition 2 are illustrated in Figure 1B. As before, suppose that there is a mass of workers with $\eta_i = \eta > 0$, and consider an average worker among them. In the case of public learning, the wage path is identical to the expected log productivity path, and its shape is concave with respect to experience (see the lines *Wage, Public* in Figure 1B). On the other hand, in the case of private learning, the wage path is different from – but converges to – the expected log productivity path, as shown in Figure 1B. The wage path is concave with respect to job tenure; therefore, the overall slope of the wage path for the new job will be similar to that of the worker's first job after leaving school (see the lines *Wage, Private* in Figure 1B). Below, we exploit the predictions in Proposition 2 to develop a test of employer learning.

2.3 Tests for Public versus Private Learning

Consider a wage equation given by

$$\begin{aligned} w_{ijt} &= g_S\left(X_{it}, T_{ijt}, S_i\right) + \omega_{ij} \\ &\quad + g_Z\left(X_{it}, T_{ijt}, S_i, Z_i\right) + \upsilon_{ijt}, \end{aligned} \tag{11}$$

where w_{ijt} is the log wage, g_S and g_Z are known functions, X_{it} is experience, T_{ijt} is tenure, S_i is years of schooling and may include other easily observable determinants of wages, Z_i is a measure of ability that is difficult for employers to observe but is available to researchers, ω_{ij} is a fixed-effect component that is the sum of the individual-specific and job-match-specific components other than Z_i, and υ_{ijt} is an idiosyncratic error component. The g_S function represents the expected log wage, conditional on X_{it}, T_{ijt}, and S_i. The g_Z function measures the deviation from the g_S function of the expected log wage conditional on X_{it}, T_{ijt}, S_i, and Z_i. Proposition 2 implies the following test: when learning is public, the g_Z function will increase at a decreasing rate with experience, whereas when learning is private, this function will increase at a decreasing rate with tenure.

Previous tests of employer learning also utilize the empirical specification based on Equation (11). For example, Farber and Gibbons (1996) and Altonji and Pierret (2001) develop a benchmark employer-learning model by imposing the following three restrictions on Equation (11): (i) assume public learning, which is equivalent to excluding T_{ijt} from the g_S and g_Z functions, (ii) exclude S_i from the g_Z function so that there is no interaction between S_i and Z_i, and (iii) exclude the fixed-effect component ω_{ij}. Under these restrictions, employer learning implies the following test: wages become more dependent on Z_i and less dependent on S_i with experience: $\partial^2_{XZ}w > 0$ and $\partial^2_{XS}w < 0$ in Equation (11).[11]

Schönberg (2007) and Pinkston (2009) extend this benchmark employer-learning model by including T_{ijt} in the g_S and g_Z functions in order to test whether employer learning is public or private. Pinkston (2009) continues to restrict the g_Z function to exclude S_i but accounts for the fixed-effect component ω_{ij} by using an instrumental variable approach. On the other hand, Schönberg (2007) no longer restricts the g_Z function but does not control for the fixed-effect component ω_{ij}. In both studies, the test for types of employer learning implies that: (*i*) in the case of public learning, wages become more dependent on Z_i and less dependent on S_i with *experience* but not with *tenure* or *employment spell length*: $\partial^2_{XZ}w > 0$, $\partial^2_{XS}w < 0$, and $\partial^2_{TZ}w = \partial^2_{TS}w = 0$ in Equation (11); and (*ii*) in the case of private learning, wages become more dependent on Z_i and less dependent on S_i with *tenure* or *employment spell length* but not with *experience*: $\partial^2_{TZ}w > 0$, $\partial^2_{TS}w < 0$, and $\partial^2_{XZ}w = \partial^2_{XS}w = 0$. In practice, in estimating the model, Schönberg (2007) and Pinkston (2009) rely on the signs of the estimates of $\partial^2_{XZ}w$ and $\partial^2_{TZ}w$ but pay less attention to the signs of the estimates of $\partial^2_{XS}w$ and $\partial^2_{TS}w$. This is because there may be other channels, such as training, that cause the effects of schooling to vary over time. We also adopt this convention in focusing on the effects of Z_i.

Although it is innovative to include tenure (or employment spell length) in addition to experience in testing for the type of employer learning, the literature on returns to tenure focuses specifically on the inclusion of tenure in a wage equation. According to the literature on returns to tenure, the OLS coefficient estimates for experience and tenure are inconsistent due to the fixed-effect component ω_{ij}. For example, Altonji and Williams (1998) argue that the OLS estimates of the wage-level equation will be inconsistent for two reasons. First, tenure is likely to be positively correlated with the fixed individual-specific component in ω_{ij} if Z_i does not include all of the factors that affect turnover behavior. In this case, the OLS estimate of the wage-tenure profile will be biased in a positive direction. Second, experience and tenure are likely to be positively correlated with the fixed job-match-specific component in ω_{ij}. The reason that tenure is positively correlated with this component is because workers are less likely to quit high-wage jobs than low-wage jobs and because employers are less likely to lay off workers with good job matches. And the reason that experience is positively correlated with this component is because job-search and matching models predict that as time passes, workers will have a higher chance of finding a job with a high job-match-specific component.

[11] See Altonji and Pierret (2001) for the details of this logic.

Because experience and tenure are positively correlated with ω_{ij}, the overall effect of ω_{ij} on the parameter estimates is unclear, but the sets of coefficients on experience and tenure are likely to be biased.

One explicit way to control for the fixed-effect component ω_{ij} is to first-difference Equation (11) for workers who stay in the same job for any two adjacent periods. This method of estimating returns to tenure was first proposed by Topel (1991).[12] However, this estimation strategy does not function properly for the previous tests of type of employer learning because $\partial^2_{XZ}w$ and $\partial^2_{TZ}w$ are not separately identified in the first-differenced model. In contrast, our test statistics, $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$, function perfectly with first-differencing. Proposition 2 adds the following conditions to the test proposed by Schönberg (2007) and Pinkston (2009): (1) $\partial^3_{X^2Z}w < 0$ and $\partial^3_{T^2Z}w = 0$ in the case of public learning; and (2) $\partial^3_{T^2Z}w < 0$ and $\partial^3_{X^2Z}w = 0$ in the case of private learning. These additional test statistics, $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$, reflect the effects of Z_i on the curvature of the wage-experience and wage-tenure profiles, respectively. Specifically, the proposed test incorporates the observation that the information-updating process slows down with either experience (in the case of public learning) or tenure (in the case of private learning).

In practice, the estimates of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$ may reflect the effects of employer learning as well as the differential wage growth path for different levels of Z_i. First, while previous studies have relied on wage equations that can be summarized by Equation (11), workers with a higher Z_i may also have steeper wage growth. For example, at some levels of experience or tenure, the g_Z function may increase at an increasing rate. Second, the empirical specification of the g_S function may fail to fully reflect the conditional expectation of the log wage. If this is the case, the gap between the g_S function and its empirical version will bias the estimates of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$. In either case, the estimates of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$ will be affected by something other than learning, and thus may overstate the true values of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$. In effect, while a positive estimate of $\partial^3_{X^2Z}w$ or $\partial^3_{T^2Z}w$ may be found in practice, a negative estimate of $\partial^3_{X^2Z}w$ or $\partial^3_{T^2Z}w$ will provide strong evidence for public or private learning, respectively.

In sum, our test of employer learning depends on two derivatives: $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$. If employer learning is public, the wage growth path of the new job (net of fixed-effects ω_{ij}) will

[12] It is also possible to estimate the model consistently if valid instrumental variables are available. Pinkston (2009) employs this approach in addressing the fixed job-match-specific component. The advantage of the first-differenced approach is that it eliminates any time-invariant unobservables in the panel data; the disadvantage, however, is that a degree of freedom is lost.

be a continuation of the wage growth path of the previous job. This implies that $\partial^3_{X^2Z} w < 0$ and $\partial^3_{T^2Z} w \geq 0$. On the other hand, if employer learning is private, the wage growth path of the new job (net of fixed-effects ω_{ij}) will be as steep as that of the job after the worker's initial labor market entry. This implies that $\partial^3_{X^2Z} w \geq 0$ and $\partial^3_{T^2Z} w < 0$.

3 Data and Descriptive Statistics

The empirical analysis is based on the 1979-2010 waves of the National Longitudinal Survey of Youth 1979 (NLSY79). This survey gathers information on a nationally representative sample of individuals living in the United States who were between the ages of 14 and 22 in 1979. Individuals were surveyed every year between 1979 and 1994 and every other year thereafter.

We restrict the analysis to white men who have completed either 12 or 16 years of education. In constructing the sample, we employ the criteria used in Altonji and Pierret (2001), Lange (2007), Pinkston (2009), and Arcidiacono, Bayer, and Hizmo (2010). We exclude labor market activities prior to the first time that an individual left school and accumulate experience from that point onward. Potential experience is constructed in terms of weeks since the respondent first left school, and actual experience is the number of weeks in which the individual worked. Tenure at a job is defined as weeks worked between the start of the job and either the date the job ended or the date the worker was interviewed for the NLSY79. Experience and tenure are divided by 50 and are thus measured in years. Following Arcidiacono, Bayer, and Hizmo (2010) and Mansour (2012), we restrict the sample to observations in which potential experience is less than 13 years.

As in many previous studies, we consider the Armed Forces Qualifying Test (AFQT) score as a variable that is correlated with worker's ability, and is observed by researchers but not by employers. The AFQT score is standardized by the age of the individual at the time of the test.

To reduce the influence of measurement error and outliers, hourly wage rates are set to missing when they are less than \$1 or above \$200 in 1987 dollars. In analyzing wage changes, we drop the samples with wages that are more than 800 percent or less than one-eighth of the previous year's value, and the samples whose education levels differ from those in the previous year.

Table 1A reports the means and standard deviations for our sample of high-school and college graduates. The average hourly wage is 8.233 dollars for high-school graduates and 12.32 dollars for college graduates. For high-school graduates, the average potential experience is 6.867 years, the average actual experience is 5.702 years, and the average tenure is 2.813 years. For college graduates, the average potential experience is 6.254 years, the average actual experience is 5.615 years, and the average tenure is 3.096 years.

Although our theoretical predictions regarding employer learning hold even if job changes are endogenous, we discuss the differences, shown in Table 1B, between those who stay in the same job for two adjacent periods and those who change jobs. Average tenure at time t for those who stay with the same employer between time $t-1$ and time t is 4.273 years for high-school graduates and 4.368 years for college graduates, whereas average tenure for those who change employers is 0.607 years for high-school graduates and 0.650 years for college graduates. On average, individuals who change employers have approximately one year less of potential experience than those who stay with the same employer, and thus individuals tend to change jobs early in their careers.

4 Evidence of Employer Learning

4.1 Empirical Specification

Many papers have pooled all of the education levels to analyze employer learning (e.g., Farber and Gibbons, 1996; Altonji and Pierret, 1997; Bauer and Haisken-DeNew, 2001; Galindo-Rueda, 2003; Lange, 2007; Light and McGee, 2014). This is equivalent to excluding S_i from the g_Z function in Equation (11). Imposing this restriction, however, is problematic if productivity enhancements differ by education. Furthermore, as Arcidiacono, Bayer, and Hizmo (2010) have shown, pooling all education levels in wage regressions leads to bias and misinterpretation of results. In particular, they find significant statistical and economic differences between high-school and college samples with regard to the coefficients on AFQT and AFQT $\times$ experience when estimating a wage-level model that does not include the tenure terms. More specifically, for high-school graduates ($S_i = 12$), they find that the coefficient on AFQT is very small and statistically insignificant but that the coefficient on AFQT interacted with experience is positive and significant. In contrast, for college graduates ($S_i = 16$), the coefficient on AFQT is large and statistically significant, whereas the coefficient on AFQT $\times$

experience is small and statistically insignificant.[13] As a result, they conclude that employers learn slowly about the ability of high-school graduates, whereas the ability of college graduates is directly revealed upon their entry into the labor market.

Schönberg (2007) also finds differences between high-school and college samples. For high-school graduates, she finds that the effect of the AFQT score on wages increases with experience but varies little with tenure, whereas for college graduates, she finds that the effect of the AFQT score increases with tenure up to the worker's fifth year in the job. In her study, she concludes that learning is largely symmetric for high-school graduates but that the results for college graduates are potentially consistent with a model of asymmetric employer learning.

Our empirical specification builds on the model in Equation (11). Consider the following wage-level equation, which applies to both high-school graduates ($S_i = 12$) and college graduates ($S_i = 16$):

$$\begin{aligned} w_{ijt} &= b_0 + b_{X1}X_{it} + b_{X2}X_{it}^2 + b_{X3}X_{it}^3 + b_{T1}T_{ijt} + b_{T2}T_{ijt}^2 + b_{T3}T_{ijt}^3 \\ &\quad + \left(b_{0Z} + b_{X1Z}X_{it} + b_{X2Z}X_{it}^2 + b_{T1Z}T_{ijt} + b_{T2Z}T_{ijt}^2\right) Z_i + \omega_{ij} + \upsilon_{ijt}. \end{aligned} \tag{12}$$

Proposition 2 implies the following test: (1) $\partial^3_{X^2Z}w = 2b_{X2Z} < 0$ and $\partial^3_{T^2Z}w = 2b_{T2Z} \geq 0$ in the case of public learning; and (2) $\partial^3_{T^2Z}w = 2b_{T2Z} < 0$ and $\partial^3_{X^2Z}w = 2b_{X2Z} \geq 0$ in the case of private learning.

As discussed in Section 2, not controlling for the fixed-effect component ω_{ij} may result in an inconsistent estimate of the test statistic. Therefore, to eliminate the fixed-effect component ω_{ij} in Equation (12), we first-difference Equation (12) for those who stay in the same job for any two adjacent periods:

$$\begin{aligned} \Delta w_{ijt} &= \beta_0 + \beta_X X_{it} + \beta_{X2}X_{it}^2 + \beta_T T_{ijt} + \beta_{T2}T_{ijt}^2 \\ &\quad + \left(\beta_{0Z} + \beta_{XZ}X_{it} + \beta_{TZ}T_{ijt}\right) Z_i + \Delta\upsilon_{ijt}. \end{aligned} \tag{13}$$

The coefficients in Equation (13) are identified, because some workers change jobs and thus for them, $X_{it} > T_{ijt}$. Since the signs of the coefficients for the quadratic terms in Equation (12) are identical to those for the linear terms in Equation (13), our test utilizes $\partial^3_{X^2Z}w = \beta_{XZ}$ and $\partial^3_{T^2Z}w = \beta_{TZ}$. Therefore, Proposition 2 implies the following test: (1) $\partial^3_{X^2Z}w = \beta_{XZ} < 0$ and $\partial^3_{T^2Z}w = \beta_{TZ} \geq 0$ in the case of public learning; and (2) $\partial^3_{T^2Z}w = \beta_{TZ} < 0$ and

[13] Using our sample, specification (1) in Appendix Tables 1A and 1B replicates the estimate of Arcidiacono, Bayer, and Hizmo (2010) for high-school graduates and college graduates, respectively. Our results are similar to theirs.

$\partial^3_{X^2Z}w = \beta_{XZ} \geq 0$ in the case of private learning. The test statistics proposed by Schönberg (2007) and Pinkston (2009), namely, b_{X1Z} and b_{T1Z}, are not separately identified, since we can estimate only the sum of the two, $\beta_{0Z} = b_{X1Z} + b_{T1Z}$.

4.2 Estimation Results

Table 2 presents the estimates of Equation (13) by restricting the sample to those who stay in the same job for any two adjacent periods. The estimates that use potential experience as the experience measure are presented in the upper panel of Table 2, and those that use actual experience are presented in the bottom panel of Table 2. For high-school graduates, the coefficient on AFQT $\times$ potential experience is -0.0285 (0.0148) and the coefficient on AFQT $\times$ tenure is 0.0101 (0.0159) as shown in specification (2) in Table 2. The coefficient on AFQT $\times$ actual experience is -0.0376 (0.0190) and the coefficient on AFQT $\times$ tenure is 0.0209 (0.0199) as shown in specification (6) in Table 2. In both specifications, the estimate of $\partial^3_{X^2Z}w$ is negative and statistically significant, whereas the estimate of $\partial^3_{T^2Z}w$ is positive but not statistically significant. Therefore, we find evidence consistent with the public learning hypothesis for high-school graduates.

Specifications (4) and (8) in Table 2 repeat the same empirical analyses for college graduates. In specification (4) in Table 2, the coefficient on AFQT $\times$ potential experience is 0.545 (0.0300) and the coefficient on AFQT $\times$ tenure is -0.1041 (0.0433). In specification (8) in Table 2, the coefficient on AFQT $\times$ actual experience is 0.0475 (0.0362) and the coefficient on AFQT $\times$ tenure is -0.1015 (0.0456). The estimate of $\partial^3_{T^2Z}w$ is negative and statistically significant, whereas the estimate of $\partial^3_{X^2Z}w$ is positive, but its significance depends on the specification. As discussed in Section 2, although it is possible to obtain a positive estimate of $\partial^3_{X^2Z}w$, the negative estimate of $\partial^3_{T^2Z}w$ suggests that learning is private for college graduates.

Therefore, we conclude that employer learning is public for high-school graduates and private for college graduates.[14] Our results accord with DeVaro and Waldman (2012), a study of how the signaling role of promotion varies with workers' education levels; it presents

[14] Light and McGee (2016) argues that the experience measure of Arcidiacono, Bayer, and Hizmo (2010) overstates the experience of workers who are college graduates relative to those who are high school graduates. Utilizing Light and McGee's experience measure, we conduct the same analysis. For high school graduates, the coefficient on AFQT $\times$ actual experience is -0.0180 (0.0178), and the coefficient on AFQT $\times$ tenure is 0.0095 (0.0193), while for college graduates, the coefficient on AFQT $\times$ actual experience is 0.0218 (0.0342), and the coefficient on AFQT $\times$ tenure is -0.0562 (0.0410). The signs of the coefficients follow the same pattern as those of our experience measures. Therefore, the measurement issue in experience appears not to be a problem of bias.

evidence that supports asymmetric learning for bachelor's and master's degree holders but not for high-school graduates and Ph.D. holders.

Although our test provides additional evidence regarding the type of employer learning, it is also of interest to examine whether the signs of the estimates of $\partial^2_{XZ}w$, $\partial^2_{TZ}w$, $\partial^3_{X^2Z}w$, and $\partial^3_{T^2Z}w$ from the wage-level model in Equation (12) are consistent with our predictions. The estimates of $\partial^2_{XZ}w$ and $\partial^2_{TZ}w$ have been examined by Schönberg (2007) using the wage-level model. She finds that the estimate of $\partial^2_{XZ}w$ for high-school graduates is positive and statistically significant, while the estimate of $\partial^2_{TZ}w$ for college graduates is positive up to the fifth year in the job. We estimate $\partial^2_{XZ}w$, $\partial^2_{TZ}w$, $\partial^3_{X^2Z}w$, and $\partial^3_{T^2Z}w$ using the instrumental variable approach proposed by Pinkston (2009).[15] The results are shown in specification (4) of Appendix Table 1A for high-school graduates and Appendix Table 1B for college graduates. For high-school graduates, we find that the estimate of $\partial^2_{XZ}w$ is positive until 8.3 years of experience, and the estimate of $\partial^3_{X^2Z}w$ is negative. On the other hand, for college graduates, although the estimates are no longer significant, the estimate of $\partial^2_{TZ}w$ is positive until 7.7 years of tenure, and the estimate of $\partial^3_{X^2Z}w$ is negative.[16] Therefore, we find patterns consistent with our predictions even from the estimates of the wage-level model.

When Altonji and Pierret (2001) test for employer learning with statistical discrimination, they also build a training model to control for the effects of nonneutral general human capital accumulation (with respect to Z_i and S_i) in the wage equation. As discussed in Section 2, our estimates of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$ may be affected by the correlations of AFQT and human capital accumulations other than employer learning, and thus the estimates of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$ may be biased estimates of the true effect of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$. Therefore, following Altonji and Pierret (2001), we add current training R_t and lag training R_{t-1} in Equation (13) to examine whether introducing these training measures alters the estimates of $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$.[17] The results, presented in specifications (2) and (4) in Table 3 that uses potential experience as the experience measure and specifications (6) and (8) in Table 3 that uses actual

[15]Pinkston (2009) uses potential experience as an instrument for actual experience. Following Abraham and Farber (1987), he uses the residual from a regression of tenure on completed job duration as an instrument for tenure. This instrument is valid, provided the completed duration of jobs controls for all the match-specific error components related to productivity.

[16]Note that 93 percent of the sample lies within 7.7 years on the job.

[17]In constructing the tenure variables, we follow Altonji and Pierret (2001). Altonji and Pierret (2001) estimate a first-differenced wage model that includes training and lag training. They find evidence suggesting a role for both human capital and employer learning with statistical discrimination. However, they cannot make a precise statement about the relative importance of these two factors, because the training data in the NLSY are weak.

experience, indicate that adding the training measures has little impact on the coefficients on AFQT, AFQT $\times$ experience, and AFQT $\times$ tenure. Furthermore, the coefficients on the training measures are all insignificant.[18] Although the training data in the NLSY97 is weak, as indicated by Altonji and Pierret (2001), the results in Table 3 are in line with our findings that employer learning is public for high-school graduates and private for college graduates.

5 Robustness Checks

In this section, we conduct several robustness checks to verify our findings. First, we examine whether there is evidence of learning over spells of continuous employment, as predicted by Pinkston (2009); that is, whether the information accumulated by an employer is transmitted to the next employer in a job-to-job transition. Next, we explore whether job changes due to quits and layoffs affect the learning process differently, since layoffs can deliver additional information about the productivity of a worker. Lastly, we examine whether our empirical patterns can be explained by other alternative models, such as learning about job match quality.

5.1 Employer Learning over Job Tenure or Employment Spell

Pinkston (2009) presents a theoretical model that shows that the private learning of employers is reflected in wages over spells of continuous employment. In his model, when there is a job change, the new employer observes the reservation wage offer of the previous employer, but not the worker's entire performance history. Therefore, the wage growth path becomes steeper after a job change, even when the spell of employment is continuous. As a robustness check, we examine whether there is a possibility of private learning by employers over spells of continuous employment.

Table 4 adds AFQT $\times$ spell length, spell length, and its squared to the specification used in Table 2. For high-school graduates, the results for which potential experience is used as the experience measure are presented in specification (1) in Table 4, and those for which actual experience is used are in specification (3) in Table 4. In specification (1) in Table 4, the coefficient on AFQT $\times$ potential experience is -0.0386 (0.0182), the coefficient on AFQT $\times$

[18] Although the estimates are insignificant, the coefficient on current training is negative for college graduates, and therefore the sign is consistent with a human capital model. However, for high-school graduates, the coefficient on current training is positive; the sign is therefore consistent with a pattern in which employers are learning about the productivity of workers and training opportunities are given to the productive workers.

tenure is -0.0170 (0.0156), and the coefficient on AFQT $\times$ spell length is 0.0374 (0.0212). In specification (3) in Table 4, the coefficient on AFQT $\times$ actual experience is -0.0692 (0.0293), the coefficient on AFQT $\times$ tenure is -0.0150 (0.0156), and the coefficient on AFQT $\times$ spell length is 0.0666 (0.0299). In both specifications, the coefficient on AFQT $\times$ experience is negative and statistically significant ($\partial^3_{X^2Z}w < 0$), the coefficient on AFQT $\times$ spell length is significantly positive, and the coefficient on AFQT $\times$ tenure is negative but not significant. Therefore, for high-school graduates, the results indicate that learning is public.

Specifications (2) and (4) in Table 4 present the results of the same analyses for college graduates. In specification (2) in Table 4, the coefficient on AFQT $\times$ potential experience is 0.0302 (0.0311), the coefficient on AFQT $\times$ tenure is -0.1279 (0.0570), and the coefficient on AFQT $\times$ spell length is 0.0501 (0.0554). The signs of the estimates in specification (4) in Table 4 are the same as in specification (2) in Table 4; that is, the coefficient on AFQT $\times$ tenure is negative and statistically significant, and the coefficients on both AFQT $\times$ actual experience and AFQT $\times$ spell length are positive and not statistically significant. Therefore, the results for college graduates imply that employers privately learn about workers over the workers' tenure rather than over spells of continuous employment.

5.2 Quits, Layoffs, and Employer Learning

Employer learning may vary depending on whether a job change is induced by a quit or a layoff, since the reason a worker leaves a previous job may affect whether a new employer learns from the worker's past outcomes. For example, if workers quit their previous jobs or are displaced from their previous jobs by plant closings, and move to a new job, employer learning may be private. However, if workers are laid off, employer learning may be public (as layoffs signal that workers are lemons and all employers acquire this information, as discussed in Gibbons and Katz (1991)). To see this point, we identify quits and layoffs and estimate the first-differenced model separately for those who quit and for those who are laid off. We assign $Q_{ijt} = 1$ if a worker starts job j after quitting his/her previous job, and $L_{ijt} = 1$ if a worker starts job j after having been laid off. We then estimate the following equation for individuals who stay in the same job for two adjacent periods, conducting separate estimations for high-school and college graduates:

$$\begin{aligned}\Delta w_{ijt} &= \left(\beta_{0Q} + \beta_{XQ}X_{it} + \beta_{X2Q}X_{it}^2 + \beta_{TQ}T_{ijt} + \beta_{T2Q}T_{it}^2\right) Q_{ijt} \\ &+ \left(\beta_{0L} + \beta_{XL}X_{it} + \beta_{X2L}X_{it}^2 + \beta_{TL}T_{ijt} + \beta_{T2L}T_{it}^2\right) L_{ijt} \\ &+ \left(\beta_{0ZQ} + \beta_{XZQ}X_{it} + \beta_{TZQ}T_{ijt}\right) Z_iQ_{ijt} \\ &+ \left(\beta_{0ZL} + \beta_{XZL}X_{it} + \beta_{TZL}T_{ijt}\right) Z_iL_{ijt} + \Delta v_{it}. \end{aligned} \quad (14)$$

Table 5 presents the estimates of Equation (14). For high-school graduates who work in jobs that began after they quit their previous job, the estimate of $\partial^3_{X^2Z}w$ is -0.0344 (0.0261), and the estimate of $\partial^3_{T^2Z}w$ is 0.0345 (0.0338); for those whose new jobs started due to layoffs, the estimate of $\partial^3_{X^2Z}w$ is -0.0528 (0.0369), and the estimate of $\partial^3_{T^2Z}w$ is 0.0920 (0.0415).[19] The signs of the estimates of $\partial^3_{X^2Z}w$ are negative for both quits and layoffs, although the estimates are not statistically significant. The signs of the estimates of $\partial^3_{T^2Z}w$ are positive for both quits and layoffs; the estimate for quits is insignificant, while that for layoffs is significant. For high-school graduates, the signs of the estimates appear to be consistent with the public learning hypothesis.

For college graduates who work in jobs that started when they quit their previous jobs, the estimate of $\partial^3_{X^2Z}w$ is 0.0955 (0.0385), and the estimate of $\partial^3_{T^2Z}w$ is -0.1064 (0.0548). Because the sign of the estimate of $\partial^3_{T^2Z}w$ is significantly negative and that of the estimate of $\partial^3_{X^2Z}w$ is positive for workers who quit their previous jobs, our results support our earlier prediction that for such workers, employer learning is private. On the other hand, for college graduates whose new jobs started due to layoffs, the estimate of $\partial^3_{X^2Z}w$ is 0.0466 (0.0911), and the estimate of $\partial^3_{T^2Z}w$ is -0.0106 (0.0765). The estimate of $\partial^3_{T^2Z}w$ is small and insignificant but negative, because the layoffs in the NLSY79 sample include job losses as a result of plant closings. For the period after 1984, however, the layoff sample *can* be separated into layoffs and job losses due to plant closings. In the college graduate sample, for quits, the estimate of $\partial^3_{X^2Z}w$ is 0.1060 (0.0440), and the estimate of $\partial^3_{T^2Z}w$ is -0.1468 (0.0443); for plant closings, the estimate of $\partial^3_{X^2Z}w$ is 0.6301 (0.2246), and the estimate of $\partial^3_{T^2Z}w$ is -0.7168 (0.3539); and for layoffs, the estimate of $\partial^3_{X^2Z}w$ is 0.0130 (0.1391), and the estimate of $\partial^3_{T^2Z}w$ is 0.0536 (0.1791). The signs are consistent with Gibbons and Katz's (1991) model, which predicts that employer learning is private for workers displaced from their previous jobs by plant closings

[19] Here, we report estimates that use potential experience as the experience measure. The sign and statistical significance are the same regardless of whether we use potential or actual experience as the experience measure (see Table 5).

(because $\partial^3_{T^2Z}w < 0$ and $\partial^3_{X^2Z}w \geq 0$). However, the results for laid-off workers are inconclusive (because $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$ are both positive).

5.3 Learning about Job-Match Quality

In Table 2, the estimate of $\partial^3_{T^2Z}w$ for college graduates is negative, implying that the wage growth path becomes steeper after workers change jobs. This empirical pattern is consistent with the situation in which employer learning about η_i is private, and in which employer j observes job-match-specific productivity, ω_{ij}. However, this empirical pattern may also be consistent with a situation in which employer learning about η_i is public, and in which employer j learns about ω_{ij}.

Suppose that workers' job-match-specific productivity is not initially observed by new employers. Consider further two workers who change their employers: one finds a job within the same occupation and the other takes a different occupation. It would be natural to assume that the new employer can better observe the worker's job-match-specific productivity when job changes occur within the same occupation. In this case, the wage growth path after a job change will be steeper when the worker's occupation is different from his/her previous job.

For college graduates, we estimate $\partial^3_{T^2Z}w$ separately for those whose occupations (at the one-digit level) differ before and after they change jobs and for those whose occupations remain the same. The coefficient on AFQT $\times$ tenure $\times$ different occupation is -0.1253 (0.0590), and the coefficient on AFQT $\times$ tenure $\times$ same occupation is -0.1615 (0.0617). Both estimates are negative and statistically significant, and the test of two equal estimates against the latter being more negative than the former produces a p-value of 20 percent. This magnitude, although not significant, is consistent with the hypothesis that the wage growth path after a job change increases at a decreasing rate, and that the wage growth path is steeper even when the occupation remains the same after the job change. This evidence provides some support for private employer learning as opposed to learning about the match quality over job tenure.

6 Concluding Remarks

This paper has taken a new approach to identifying types of employer learning. In our model, an employer forms expectations about the productivity of workers based on available information and then updates his or her expectations in response to new information being revealed. When workers change jobs, the quantity of information available to a new employer will differ depending on whether learning is public or private, and the type of learning will affect the amount of additional information the new employer gains. In this paper, we demonstrate how these differences in the amount of information available to the new employer at the time of the job change and over the job tenure relate to returns to experience and tenure. If employer learning is public, the wage growth path in a new job will be a continuation of the wage growth path in the previous job. In contrast, if learning is private, the wage growth path in a new job will be as steep as it was for the first job at the time of labor market entry.

We test the implications of our theoretical model by using the sample of individuals in the NLSY79 who stay in the same job for two adjacent periods. Our results are consistent with public learning for high-school graduates and private learning for college graduates. Specifically, for high-school graduates, the contribution to wages of factors observed only by researchers (e.g., the AFQT score) increases at a decreasing rate with experience but not with tenure. Therefore, the wage growth path in a new job is a continuation of the wage growth path in the previous job, so that for high-school graduates, workers' information is perfectly transferred to outside firms. In contrast, for college graduates, the contribution to wages of factors observed only by researchers increases at a decreasing rate with tenure but not with experience. Thus, the wage growth path in a new job will be closer to that of the first job at the time of labor market entry, so that for college graduates, information is not transferred to outside firms.

Figures

Figure 1A: Expected Productivity when $f(H_{ijt}) = 0$.

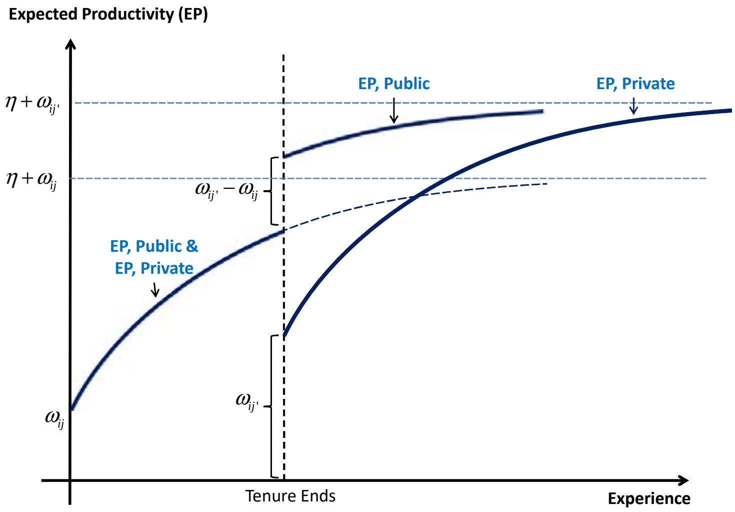
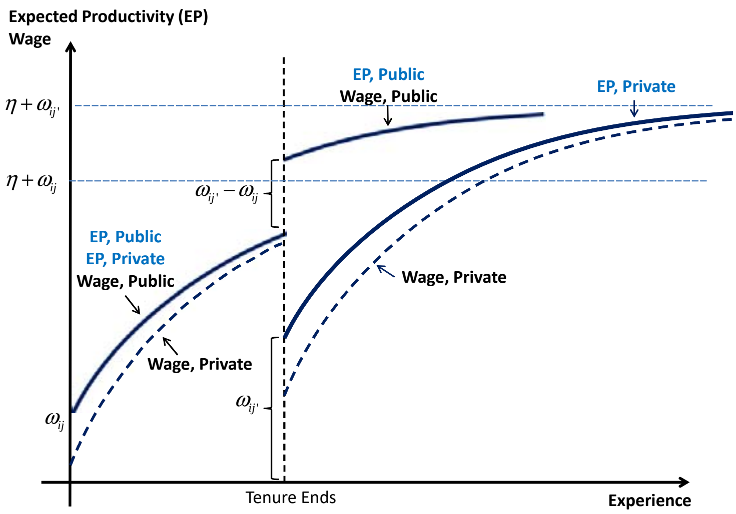


Figure 1B: Expected Productivity and Wages when $f\left(H_{ijt}\right) = 0$.



Tables

Table 1A. Summary Statistics

	High-School Graduates		College Graduates	
	Mean	SD	Mean	SD
Real Hourly Wage	8.233	4.774	12.32	8.934
Log of Real Hourly Wage	1.999	0.459	2.373	0.511
Standardized AFQT	-0.057	0.830	0.796	0.501
Potential Experience	6.867	3.628	6.254	3.631
Actual Experience	5.702	3.408	5.615	3.467
Tenure	2.813	2.809	3.096	2.925

Notes: Wages are in 1987 dollars. Experience and tenure are measured in years.
There are 10,432 observations for high-school graduates and 4,013 observations for college graduates.
The number of individuals is 1,485 for high-school graduates and 583 for college graduates.

Table 1B. Summary Statistics based on whether Job Changed between Two Adjacent Periods

	High-School Graduates			
	Same Job between t and $t-1$		Change Jobs between t and $t-1$	
	Mean	SD	Mean	SD
Real Hourly Wage	8.946	3.964	7.292	3.957
Log of Real Hourly Wage	2.106	0.418	1.882	0.445
Change in Log Wage	0.045	0.258	0.041	0.452
Standardized AFQT	-0.042	0.833	-0.078	0.817
Potential Experience	7.778	3.257	6.734	3.389
Actual Experience	6.790	3.104	5.206	3.035
Tenure	4.273	2.747	0.607	0.712

	College Graduates			
	Same Job between t and $t-1$		Change Jobs between t and $t-1$	
	Mean	SD	Mean	SD
Real Hourly Wage	12.94	6.446	11.01	5.748
Log of Real Hourly Wage	2.459	0.451	2.273	0.508
Change in Log Wage	0.061	0.261	0.081	0.470
Standardized AFQT	0.806	0.497	0.751	0.505
Potential Experience	7.043	3.314	5.837	3.484
Actual Experience	6.499	3.188	5.034	3.228
Tenure	4.368	2.833	0.650	0.686

Notes: For high-school graduates, there are 5,652 observations for workers who worked at the same job between two adjacent periods and 2,671 observations for workers who changed jobs between two adjacent periods. For college graduates, the numbers are 2,479 and 794, respectively.

Table 2. The Effects of AFQT on the Change in Log Wages by Experience and Tenure
Sample: Individuals who stay in the same job for two adjacent periods

Use Potential Experience as Experience Measure

Dependent Variable: $\Delta \log wage$	High-School Graduates		College Graduates	
Independent Variables:	(1)	(2)	(3)	(4)
AFQT	0.0092**	0.0266**	0.0228**	0.0316
	(0.0034)	(0.0085)	(0.0086)	(0.0202)
AFQT×Potential Experience/10		-0.0285*		0.0545*
		(0.0148)		(0.0300)
AFQT×Tenure/10		0.0101		-0.1041**
		(0.0159)		(0.0433)
Potential Experience	-0.0075	-0.0070	-0.0137*	-0.0181**
	(0.0059)	(0.0058)	(0.0081)	(0.0088)
Potential Experience^2/10	0.0032	0.0027	0.0087	0.0087
	(0.0038)	(0.0038)	(0.0054)	(0.0054)
Tenure	-0.0127**	-0.0127**	0.0092	0.0174**
	(0.0047)	(0.0047)	(0.0069)	(0.0078)
Tenure^2/10	0.0054	0.0055	-0.0100*	-0.0102*
	(0.0038)	(0.0038)	(0.0057)	(0.0056)
Adj R-squared	0.0075	0.0079	0.0075	0.0089
Observations	5,652	5,652	2,479	2,479

Use Actual Experience as Experience Measure

Dependent Variable: $\Delta \log wage$	High-School Graduates		College Graduates	
Independent Variables:	(5)	(6)	(7)	(8)
AFQT	0.0094**	0.0249**	0.0220**	0.0370*
	(0.0034)	(0.0079)	(0.0087)	(0.0206)
AFQT×Actual Experience/10		-0.0376**		0.0475
		(0.0190)		(0.0362)
AFQT×Tenure/10		0.0209		-0.1015**
		(0.0199)		(0.0456)
Actual Experience	-0.0021	-0.0023	-0.0118	-0.0148
	(0.0057)	(0.0057)	(0.0094)	(0.0102)
Actual Experience^2/10	-0.0004	-0.0004	0.0069	0.0063
	(0.0038)	(0.0038)	(0.0066)	(0.0066)
Tenure	-0.0133**	-0.0131**	0.0094	0.0171**
	(0.0049)	(0.0049)	(0.0073)	(0.0082)
Tenure^2/10	0.0064	0.0064	-0.0098	-0.0097
	(0.0040)	(0.0040)	(0.0061)	(0.0060)
Adj R-squared	0.0073	0.0078	0.0074	0.0084
Observations	5,652	5,652	2,479	2,479

Notes: White/Huber standard errors clustered at the individual level are in parentheses. All specifications control for year effects. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3. The Effects of AFQT on the Change in Log Wages by Experience and Tenure with Controls for Training

Sample: Individuals who stay in the same job for two adjacent periods

Use Potential Experience as Experience Measure

Dependent Variable: $\Delta \log wage$	High-School Graduates		College Graduates	
Independent Variables:	(1)	(2)	(3)	(4)
AFQT	0.0252**	0.0252**	0.0300	0.0304
	(0.0087)	(0.0087)	(0.0210)	(0.0210)
AFQT×Potential Experience/10	-0.0255*	-0.0253*	0.0613**	0.0614**
	(0.0148)	(0.0149)	(0.0296)	(0.0296)
AFQT×Tenure/10	0.0086	0.0083	-0.1215**	-0.1217**
	(0.0163)	(0.0163)	(0.0399)	(0.0399)
Potential Experience	-0.0045	-0.0047	-0.0176**	-0.0179**
	(0.0058)	(0.0058)	(0.0082)	(0.0083)
Potential Experience^2/10	0.0014	0.0015	0.0082	0.0084
	(0.0038)	(0 0038)	(0.0052)	(0.0052)
Tenure	-0.0121**	-0.0121**	0.0199**	0.0204**
	(0.0048)	(0.0048)	(0.0075)	(0.0076)
Tenure^2/10	0.0048	0.0049	-0.0106*	-0.0110*
	(0.0039)	(0.0039)	(0.0056)	(0.0057)
Training		0.0235		-0.0159
		(0.0174)		(0.0166)
Lag Training		-0.0235		0.0077
		(0.0300)		(0.0160)
R-squared	0.0073	0.0072	0.0109	0.0104
Observations	5,461	5,461	2380	2380

Use Actual Experience as Experience Measure

Dependent Variable: $\Delta \log wage$	High-School Graduates		College Graduates	
Independent Variables:	(5)	(6)	(7)	(8)
AFQT	0.0245**	0.0245**	0.0365*	0.0369*
	(0.0080)	(0.0080)	(0.0213)	(0.0213)
AFQT×Actual Experience/10	-0.0366*	-0.0363*	0.0534	0.0533
	(0.0190)	(0.0190)	(0.0358)	(0.0358)
AFQT×Tenure/10	0.0206	0.0202	-0.1189**	-0.1188**
	(0.0204)	(0.0204)	(0.0422)	(0.0422)
Actual Experience	-0.0011	-0.0013	-0.0147	-0.0150
	(0.0057)	(0.0057)	(0.0095)	(0.0096)
Actual Experience^2/10	-0.0010	-0.0009	0.0062	0.0064
	(0.0038)	(0.0038)	(0.0062)	(0.0063)
Tenure	-0.0123**	-0.0123**	0.0197**	0.0202**
	(0.0050)	(0.0050)	(0.0080)	(0.0081)
Tenure^2/10	0.0055	0.0055	-0.0103*	-0.0107*
	(0.0041)	(0.0041)	(0.0061)	(0.0061)
Training		0.0227		-0.0161
		(0.0175)		(0.0166)
Lag Training		-0.0227		0.0075
		(0.0299)		(0.0160)
R-squared	0.0075	0.0074	0.0103	0.0098
Observations	5,461	5,461	2380	2380

Notes: White/Huber standard errors clustered at the individual level are in parentheses. All specifications control for year effects. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 4. The Effects of AFQT on the Change in Log Wages by Experience, Tenure, and Spell Length

Sample: Individuals who stay in the same job for two adjacent periods

	Use Potential Experience as Experience Measure		Use Actual Experience as Experience Measure	
Dependent Variable: $\Delta \log wage$	High–School Graduates	College Graduates	High–School Graduates	College Graduates
Independent Variables:	(1)	(2)	(3)	(4)
AFQT	0.0271**	0.0310	0.0270**	0.0375*
	(0.0086)	(0.0202)	(0.0081)	(0.0204)
AFQT×Experience/10	-0.0386**	0.0302	-0.0692**	0.0060
	(0.0182)	(0.0311)	(0.0293)	(0.0413)
AFQT×Tenure/10	-0.0170	-0.1279**	-0.0150	-0.1260**
	(0.0156)	(0.0570)	(0.0156)	(0.0570)
AFQT×Spell Length/10	0.0374*	0.0501	0.0666**	0.0665
	(0.0212)	(0.0554)	(0.0299)	(0.0604)
Experience	-0.0073	-0.0097	-0.0031	-0.0007
	(0.0061)	(0.0091)	(0.0063)	(0.0115)
Experience^2/10	0.0031	0.0046	0.0003	-0.0015
	(0.0040)	(0.0057)	(0.0046)	(0.0078)
Tenure	-0.0134**	0.0253**	-0.0135**	0.0253**
	(0.0060)	(0.0099)	(0.0060)	(0.0100)
Tenure^2/10	0.0067	-0.0147**	0.0068	-0.0148**
	(0.0047)	(0.0069)	(0.0047)	(0.0069)
Spell Length	0.0011	-0.0169	0.0008	-0.0227*
	(0.0063)	(0.0114)	(0.0066)	(0.0122)
Spell Length^2/10	-0.0018	0.0091	-0.0009	0.0133
	(0.0046)	(0.0076)	(0.0050)	(0.0084)
R-squared	0.0078	0.0084	0.0083	0.0083
Observations	5,652	2,479	5,652	2,479

Notes: White/Huber standard errors clustered at the individual level are in parentheses. All specifications control for year effects. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5. The Effects of AFQT on the Change in Log Wages by Experience and Tenure
Sample: Individuals who stay in the same job for two adjacent periods

	Use Potential Experience as Experience Measure		Use Actual Experience as Experience Measure	
Dependent Variable: $\Delta \log wage$	High-School Graduates	College Graduates	High-School Graduates	College Graduates
Independent Variables:	(1)	(2)	(3)	(4)
Quit	0.0412	-0.1061	0.0357	-0.0815
	(0.0562)	(0.1032)	(0.0504)	(0.0978)
Quit×AFQT	0.0237	0.0128	0.0220	0.0212
	(0.0179)	(0.0206)	(0.0159)	(0.0209)
Layoff×AFQT	0.0070	-0.0314	-0.0101	-0.0272
	(0.0253)	(0.0646)	(0.0234)	(0.0633)
Quit×AFQT×Experience/10	-0.0344	0.0955**	-0.0413	0.0854*
	(0.0261)	(0.0385)	(0.0322)	(0.0446)
Quit×AFQT×Tenure/10	0.0345	-0.1064*	0.0421	-0.1029*
	(0.0338)	(0.0548)	(0.0396)	(0.0592)
Layoff×AFQT×Experience/10	-0.0528	0.0466	-0.0353	0.0577
	(0.0369)	(0.0911)	(0.0364)	(0.01022)
Layoff×AFQT×Tenure/10	0.0920**	-0.0106	0.0860**	-0.0293
	(0.0415)	(0.0765)	(0.0406)	(0.0833)
Quit×Experience	-0.0105	-0.0228**	-0.0105	-0.0225*
	(0.0095)	(0.0105)	(0.0093)	(0.0116)
Quit×Experience^2/10	0.0046	0.0092	0.0045	0.0103
	(0.0059)	(0.0069)	(0.0059)	(0.0079)
Quit×Tenure	-0.0159**	0.0187*	-0.0145*	0.0200*
	(0.0074)	(0.0105)	(0.0077)	(0.0110)
Quit×Tenure^2/10	0.0087	-0.0122	0.0079	-0.0140*
	(0.0064)	(0.0078)	(0.0065)	(0.0083)
Layoff×Experience	-0.0026	-0.0141	-0.0010	0.0042
	(0.0130)	(0.0207)	(0.0131)	(0.0226)
Layoff×Experience^2/10	0.0009	0.0068	-0.0026	-0.0076
	(0.0081)	(0.0120)	(0.0092)	(0.0138)
Layoff×Tenure	-0.0172	-0.0126	-0.0151	-0.0199
	(0.0121)	(0.0174)	(0.0122)	(0.0180)
Layoff×Tenure^2/10	0.0121	0.0021	0.0122	0.0100
	(0.0107)	(0.0131)	(0.0107)	(0.0135)
R-squared	0.0048	0.0110	0.0046	0.0104
Observations	3,166	1,641	3,166	1,641

Notes: White/Huber standard errors clustered at the individual level are in parentheses. All specifications control for year effects. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix

Appendix Table 1A. The Effects of AFQT by Experience and Tenure on Log Wages
Sample: High-School Graduates

Dependent Variable: log *wage*	OLS	OLS	IV	IV
Independent Variables:	(1)	(2)	(3)	(4)
AFQT	0.0179	0.0220	0.0231*	0.0233
	(0.0127)	(0.0166)	(0.0129)	(0.0202)
AFQT×Pot. Experience/10	0.0845**	0.0676		
	(0.0166)	(0.0556)		
AFQT×Pot. Experience^2/100		0.0126		
		(0.0403)		
AFQT×Actual Experience/10			0.1024**	0.3314**
			(0.0323)	(0.1398)
AFQT×Actual Experience^2/100				-0.1987*
				(0.1206)
AFQT×Tenure/10			-0.0710	-0.4712*
			(0.0528)	(0.2420)
AFQT×Tenure^2/100				0.4354*
				(0.2531)
Pot. Experience/10	0.1005**	0.1005**		
	(0.0118)	(0.0118)		
Pot. Experience^2/100	-0.0429**	-0.0431**		
	(0.0202)	(0.0201)		
Pot. Experience^3/1000	0.0078	0.0079		
	(0.0100)	(0.0100)		
Actual Experience/10			0.3408**	0.3410**
			(0.0723)	(0.0721)
Actual Experience^2/100			-0.5130**	-0.5101**
			(0.1458)	(0.1447)
Actual Experience^3/1000			0.2531**	0.2502**
			(0.0788)	(0.0778)
Tenure/10			-0.5301**	-0.5324**
			(0.1664)	(0.1665)
Tenure^2/100			1.3217**	1.3227**
			(0.3967)	(0.3958)
Tenure^3/1000			-0.8003**	-0.7991**
			(0.2358)	(0.2348)
R-squared	0.1441	0.1440	0.0071	0.0061
Observations	10,131	10,131	10,131	10,131

Note: White/Huber standard errors clustered at the individual level are in parentheses. All specifications control for urban residence, and year effects. Specifications (3) and (4) control for one-digit occupation and industry, as in Schönberg (2007).
** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix Table 1B. The Effects of AFQT by Experience and Tenure on Log Wages
Sample: College Graduates

Dependent Variable: log *wage*	OLS	OLS	IV	IV
Independent Variables:	(1)	(2)	(3)	(4)
AFQT	0.1002**	0.0791	0.0557	0.0411
	(0.0402)	(0.0525)	(0.0358)	(0.0490)
AFQT×Pot. Experience/10	0.0599	0.1570		
	(0.0570)	(0.1746)		
AFQT×Pot. Experience^2/100		-0.0763		
		(0.1302)		
AFQT×Actual Experience/10			0.0493	0.0281
			(0.0875)	(0.3843)
AFQT×Actual Experience^2/100				0.0201
				(0.3215)
AFQT×Tenure/10			0.0878	0.2365
			(0.1118)	(0.5992)
AFQT×Tenure^2/100				-0.1536
				(0.6055)
Pot. Experience/10	0.1138**	0.1055**		
	(0.0233)	(0.0270)		
Pot. Experience^2/100	-0.1296**	-0.1224**		
	(0.0379)	(0.0397)		
Pot. Experience^3/1000	0.0516**	0.0509**		
	(0.0189)	(0.0189)		
Actual Experience/10			0.0564	0.0584
			(0.1068)	(0.1000)
Actual Experience^2/100			-0.0501	-0.0524
			(0.2040)	(0.1948)
Actual Experience^3/1000			0.0173	0.0177
			(0.1080)	(0.1069)
Tenure/10			0.0467	0.0334
			(0.1985)	(0.1835)
Tenure^2/100			-0.0643	-0.0484
			(0.4499)	(0.4280)
Tenure^3/1000			0.0304	0.0281
			(0.2617)	(0.2583)
R-squared	0.1477	0.1475	0.3070	0.3073
Observations	3,827	3,827	3,827	3,827

Note: White/Huber standard errors clustered at the individual level are in parentheses. All specifications control for urban residence, and year effects. Specifications (3) and (4) control for one-digit occupation and industry, as in Schönberg (2007).
** Significant at the 5 percent level. * Significant at the 10 percent level.

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