Employer Learning, Job Mobility, and Wage Dynamics*

Seik Kim†
University of Washington

Emiko Usui‡
Nagoya University and IZA

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 wage growth paths when there is a job change, because the amount of information transferred to a new employer about workers' productivity is smaller 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 National Longitudinal Survey of Youth 1979 (NLSY79), we find that learning is primarily public.

Keywords: Employer Learning; Labor Market Information; Wage Dynamics.

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†Seik Kim, Department of Economics, University of Washington, Box 353330, Savery Hall 305, Seattle, WA 98195-3330, USA. Tel: +1-206-685-6081. Fax: +1-206-685-7477. E-mail address: seikkim@uw.edu.

‡Emiko Usui, Graduate School of Economics, Nagoya University, Nagoya, 464-8601, Japan. Tel and fax: +81-52-789-4940. E-mail address: usui@soec.nagoya-u.ac.jp.

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 workers' careers, information about their productivity will gradually be 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 the factors observed by researchers, but not by employers (e.g., test scores), will increase with workers' experience, while the contribution to wages of the factors observed by both employers and researchers (e.g., education) will decrease with workers' experience.

A common assumption made by Farber and Gibbons (1996) and Altonji and Pierret (2001) is that all employers in the market learn the same amount of information about the productivity of workers. In other words, information gathered by the 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 would be private.

Whether learning is public or private has been empirically tested in various ways. Among these approaches, 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. If incumbent employers learn more about workers' productivity than outside employers, the contribution to wages of the factors observed by researchers, but not by employers, will increase with job tenure according to Schönberg (and over a spell of continuous employment according to Pinkston); and the contribution to wages of the factors observed by both employers and researchers will decrease with job tenure for Schönberg (and over a spell of continuous employment for Pinkston). If learning is public, a similar logic holds with respect to experience rather than job tenure (or employment spell length for Pinkston).

This paper reinvestigates whether employer learning is public or private, with an emphasis on the empirical tests proposed by Schönberg (2007) and Pinkston (2009). We have two reasons for doing this. First, the empirical evidence points in different directions. Schönberg's evidence supports the public learning hypothesis, whereas Pinkston's evidence supports the private learning hypothesis.[1] The second and more important reason is that their test statistics are likely to be inconsistent. Both empirical strategies rely on the OLS estimates of experience and tenure (or employment spell length) in a wage equation, but the literature on returns to seniority suggests that these estimates are inconsistent due to fixed unobserved individual-specific and job-match-specific components. A widely used strategy to deal with this problem is first-differencing, but it is not applicable to their tests because the coefficients on experience and tenure are not separately identified in a first-differenced wage model.[2]

The main objective of this paper is to develop a testing procedure that is based on consistent estimates of experience and tenure in a wage equation. We let the employer form expectations about the productivity of workers based on available information and update his or her belief in response to new information being revealed. Using this theoretical framework, we demonstrate that public and private learning schemes make two distinct predictions about wage growth paths whenever there is a job change. In the case of public learning, the wage growth rates in the new job will be a continuation of the wage growth rates of the previous

[1] There are other approaches that test the type of employer learning. Gibbons and Katz (1991) develop and find empirical support for an asymmetric-information model of layoffs. In their model, layoffs signal that the workers are of low ability. If one assumes that job losses due to plant closings do not send such a negative signal, post-displacement wages should be lower for workers who are laid off than for those displaced by a plant closing. Their 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.

[2] Pinkston (2009) uses an IV approach to control for endogeneity. To account for the job-match heterogeneity, he regresses the length of an employment spell on the worker's career-average spell length, actual experience, tenure, and a dummy variable for missing values of tenure. He states that as long as (i) these variables control for all components of employment spell length that are correlated with productivity, and (ii) tenure controls for match-specific components that are correlated with the residual in the wage equation, the residual from this regression is a valid instrument for employment spell length.

job, although the path continuity may be broken by the job change. This implies that the contribution to wages of the factors observed only by researchers will increase at a decreasing rate with experience but will not increase with tenure. In the case of private learning, the wage growth paths in the new job will be as steep as those in the first job at the time of labor market entry. This implies that the contribution to wages of the factors observed only by researchers will increase at a decreasing rate with tenure but will not increase with experience. Since 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 the contribution to wages of the 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 is not different from what the incumbent employers have. Therefore, learning is, in general, public. We also find evidence that the transmission of learning to outside employers may depend on the type of occupation an individual holds: learning tends to be public for service workers and operatives, but private for managerial occupations.

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

2 Information and Employer Learning

2.1 Employers' Predictions of Workers' Productivity

Consider an individual i who works with an employer j and has t years of labor market experience. Worker i is characterized by i's log of productivity at job j in year t in the labor market, p_{ijt}:

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

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 components that are observed by employers but unknown to researchers (such as individual-specific and job-match-specific components), and η_i consists of other factors affecting productivity that are not observed directly by employers (such as inborn ability and test scores).[3] In this model, employers do not observe η_i, but researchers may observe a part of η_i. The distribution of η_i is common knowledge. We assume that η_i is a normal random variable with expectation zero and variance σ_η^2.

When employer j receives applications, he or she must make predictions about the unknown η_i. Predictions involve errors. This can be understood as applicants sending noisy signals of their productivity to potential employers. Let $\overrightarrow{s}_{ij}$ denote the private signal that employer j receives from applicant i about η_i at the time that j makes a new job offer to i, a signal other than 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, independent of η_i, with expectation zero and variance σ_ξ^2. Examples of $\overrightarrow{s}_{ij}$ include recommendation letters, interview results, or the latest wage offered by an incumbent employer.

Consider an individual i who completes schooling and enters the labor market for the first time. Employer j makes a prediction about worker i's productivity using all available information: H_{ij1}, ω_{ij}, and $\overrightarrow{s}_{ij}$. The employer j's expected log productivity for worker i at

[3] Both potential experience and tenure are equal to one during the first year in the labor market.

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 by using the property of multivariate normal distribution.

Once worker i and employer j are matched, worker i will start producing an output at each experience 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} to be 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 *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}, from observing a 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 at experience or tenure t will be 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 since we assume it is worker i's first job.

The last term in the second equation in (5) has important implications. First, as worker

i becomes more experienced, employer j learns more about η_i. This is because the first and second factors of the last term converge to unity and η_i, respectively, as $t \to \infty$. Second, the amount of updated information decreases with experience or tenure t. In other words, the speed of convergence slows down. To see this, it is sufficient to show that the first factor of the last term is increasing in t with 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).[4]

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 the past performance records are perfectly transferred to outside firms, we say that learning is public or symmetric. If not, we say that learning is private or asymmetric.

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 expected log productivity at

[4] 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.

experience $T+s$ and tenure s, $s \geq 2$, will be determined by

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

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

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

In later periods, the expected log productivity at experience $T+s$ and tenure s, $s \geq 2$, will be 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 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 for the average worker under public and private learning schemes when there is a job change, where $f\left(H_{ijt}\right)$ is set to zero for simplicity. Condition (6) determines that the shape of these expected log productivity paths will be concave for experience or tenure. 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 is not 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 that for the first job after leaving school (see the lines *EP, Private* in Figure 1A).

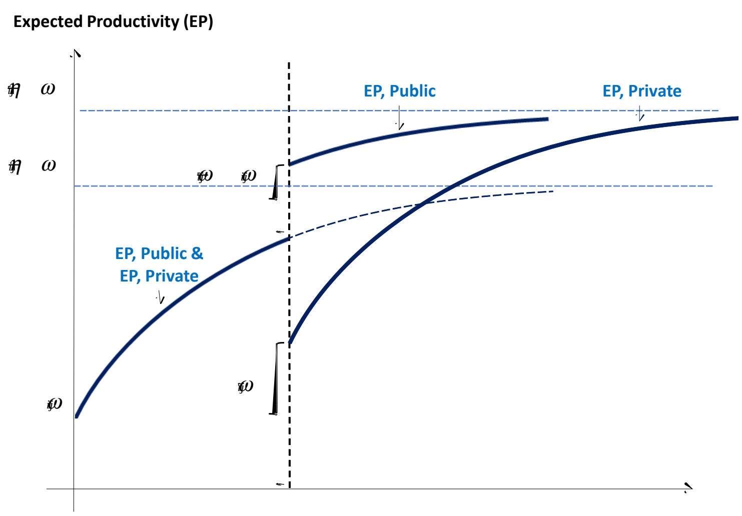

Figure 1A: Expected Productivity when $f(H_{ijt}) = 0$.

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

Although useful, the results in Proposition 1 are not directly applicable for a test of employer learning since expected log productivity is not available in the data. In the next subsection, we explore the relationship between the expected log productivity and log wages in order to develop a feasible test for 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 differ depending on whether employer learning is public or private. Let w_{ijt} be worker i's log wage at job j at experience t. In the case of public learning, the log wage is equal to the expected log productivity. This is because all employers have the same amount of information about workers, and any log wage offer below the worker's expected log productivity will be outbid by slightly higher log wage offers. Therefore, the expected log productivity equations (3), (5), (7), and (8) are also the log wage equations.

If learning is private, we can apply the logic developed in Pinkston (2009). In that setting, incumbent and outside employers compete with each other by offering wages according to an ascending auction rule. This framework is useful since the results from 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 the expected productivity; the winning employer is the employer with the highest wage offer, and the contract wage equals the second highest wage offer. This has the following implications. If a worker continues working with the current employer, the contract log wage does not exceed the log productivity as evaluated 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 be at least the current contract wage plus a natural increase in wages due to human capital accumulation, $f\left(H_{ij,t+1}\right) - f\left(H_{ijt}\right)$. If the worker decides to stay in his/her current job in the next period, the gap between the current employer's expectation of 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 the realized wages slows down. This is a sufficient condition for the increments in wage growth paths to decrease with job tenure, which is our key testing strategy. However, this follows straightforwardly from Pinkston's (2009) result. He shows that the sequence of wages converges to the sequence of the incumbent employer's expectation of the worker's productivity. Since the increments of a converging sequence converge to zero, the speed of convergence decreases with job tenure.

When a job change occurs, it implies that at least one wage offer made by outside employers exceeds the current employer's wage offer. In this case, the evaluation of the employer with the second highest wage offer is transmitted to the winning employer, although the entire performance history is not. After a job change, the wage growth paths will become 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 that 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 that in the first job because the expected value of the second highest wage offer is a function of the number of participants. In any event, we have the prediction that the wage growth path in the new job in the case of private learning will be steeper 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 paths in the new job will be a continuation of the wage growth paths in the previous job. If learning is private, the wage growth paths in the new job will become closer to those in 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 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.

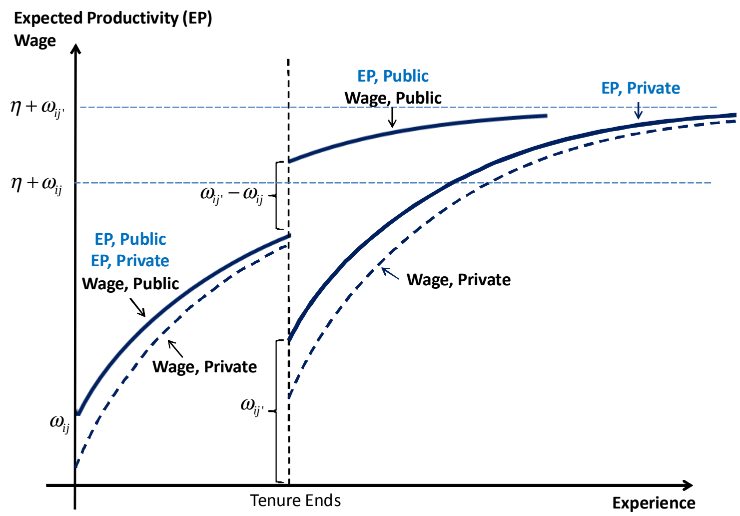

Figure 1B: Expected Productivity and Wages when $f(H_{ijt}) = 0$.

2.3 Tests for Public versus Private Learning

Our empirical specification builds on the models in previous papers by Farber and Gibbons (1996), Altonji and Pierret (2001), Pinkston (2006, 2009), Lange (2007), and Schönberg (2007). Consider this wage equation:

$$\begin{aligned} w_{ijt} &= b_0 + b_{0S}S_i + b_{0Z}Z_i + b_{X1}X_{it} + b_{X2}X_{it}^2 + b_{T1}T_{ijt} + b_{T2}T_{ijt}^2 \\ &\quad + \left(b_{X1S}X_{it} + b_{X2S}X_{it}^2 + b_{T1S}T_{ijt} + b_{T2S}T_{ijt}^2\right) S_i \\ &\quad + \left(b_{X1Z}X_{it} + b_{X2Z}X_{it}^2 + b_{T1Z}T_{ijt} + b_{T2Z}T_{ijt}^2\right) Z_i + \omega_{ij} + \upsilon_{ijt}, \end{aligned} \tag{11}$$

where X_{it} is experience, T_{ijt} is tenure, S_i is years of schooling as observed by both employers and researchers, Z_i is a measure of ability which is difficult for employers to observe but is available to researchers, ω_{ij} is a fixed-effect component which is the sum of the individual-specific and job-match-specific components other than Z_i, and υ_{ijt} is an idiosyncratic error component.

Previous tests of employer learning utilize the parameters of the wage-level equation (11), while not explicitly controlling for ω_{ij}. For example, Farber and Gibbons (1996) and Altonji and Pierret (2001) develop a benchmark learning model. They assume public learning, and impose restrictions such that all the coefficients on tenure and its interaction terms are jointly zero in Equation (11): $b_{T1} = b_{T2} = b_{T1Z} = b_{T2Z} = b_{T1S} = b_{T2S} = 0$. Under these restrictions, they argue that employer learning implies that as time passes, wages depend more on Z_i and less on S_i: $\partial^2_{XZ} w = b_{X1Z} + 2b_{X2Z}X_{it} > 0$ and $\partial^2_{XS} w = b_{X1S} + 2b_{X2S}X_{it} < 0$.[5]

Schönberg (2007) and Pinkston (2009) extend this framework to test for the type of employer learning.[6] They argue that public learning implies that wages depend more on Z_i and less on S_i with *experience*, but do not depend on *tenure* (or *employment spell length*): $\partial^2_{XZ} w = b_{X1Z} + 2b_{X2Z}X_{it} > 0$, $\partial^2_{XS} w = b_{X1S} + 2b_{X2S}X_{it} < 0$, and $\partial^2_{TZ} w = \partial^2_{TS} w = 0$ in Equation (11). On the other hand, private learning implies that wages depend more on Z_i and less on S_i with *tenure* (or *employment spell length*), but do not depend on *experience*: $\partial^2_{TZ} w = b_{T1Z} + 2b_{T2Z}T_{ijt} > 0$, $\partial^2_{TS} w = b_{T1S} + 2b_{T2S}T_{ijt} < 0$, and $\partial^2_{XZ} w = \partial^2_{XS} w = 0$.[7] In practice, however, both Schönberg and Pinkston rely on the results coming from Z_i. This is because there may be other channels, such as training, that cause the effects of education to

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

[6] 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 correlated with the worker's ability as the spell of the worker's continuous employment increases, rather than as the worker's labor market experience increases. Thus, Pinkston estimates the wage-level model in Equation (11) by replacing tenure with employment spell length.

[7] The effect of human capital accumulation will be reflected in the coefficients b_{X1}, b_{X2}, b_{T1}, and b_{T2}. However, if productivity enhancements differ by education, it will be a problem to simply estimate Equation (11). Schönberg (2007) separates the sample into $S_i = 12$ (high school graduates) and $S_i = 16$ (college graduates) to solve this problem.

vary over time.

Not controlling for ω_{ij} in testing the type of employer learning, however, may result in inconsistent estimation of the test statistic. According to the literature on returns to seniority, the OLS estimates of the wage-level equation (11) are inconsistent due to fixed unobserved individual-specific and job-match-specific components 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 the factors that affect turnover behavior. The OLS estimate of the wage-tenure profile will then be biased in a positive direction. Second, experience and tenure are likely to be positively correlated with the fixed job-match error component in ω_{ij}. It is positively correlated with tenure because workers are less likely to quit high-wage jobs than low-wage jobs, and firms are less likely to lay off workers with a good job match. It is also positively correlated with experience since job-search and matching models predict that workers have more of a chance to find a job with a high job-match error component. Since experience and tenure are positively correlated with ω_{ij}, the overall effect of ω_{ij} on the parameters in Equation (11) is unclear, but they are likely to be biased.

Consistent estimates of the parameters in Equation (11) may be obtained by first-differencing, but previous test statistics of employer learning are not identified in a first-differenced model. The test statistic we propose is different from those in the above-mentioned papers in that ω_{ij} is explicitly controlled for and survives first-differencing. The test implied by Proposition 2 adds the conditions of $\partial^3_{X^2Z}w = b_{X2Z} < 0$ and $\partial^3_{T^2Z}w = b_{T2Z} = 0$ in the case of public learning, and $\partial^3_{T^2Z}w = b_{T2Z} < 0$ and $\partial^3_{X^2Z}w = b_{X2Z} = 0$ in the case of private learning.[8] The conditions, $\partial^3_{X^2Z}w$ and $\partial^3_{T^2Z}w$, reflect the effects of AFQT on the curvature of the wage-experience and wage-tenure profiles, respectively. These ad-

[8] As in Schönberg (2007) and Pinkston (2009), we pay less attention to the theoretical predictions of $\partial^3_{X^2S}w = b_{X2S} > 0$ and $\partial^3_{T^2S}w = b_{T2S} = 0$ in the case of public learning, and $\partial^3_{T^2S}w = b_{T2S} > 0$ and $\partial^3_{X^2S}w = b_{X2S} = 0$ in the case of private learning.

ditional conditions are important because of the following two reasons. First, the proposed test incorporates the observation that the information-updating process slows down with either experience or tenure. Second, the additional conditions survive first-differencing, and the individual-specific and the job-match-specific components can be accounted for. To see this point, consider a first-differenced model for those who stay in the same job for any two adjacent periods:[9]

$$\begin{aligned}\Delta w_{ijt} &= \beta_0 + \beta_X X_{it} + \beta_T T_{ijt} \\ &\quad + \left(\beta_{0S} + \beta_{XS} X_{it} + \beta_{TS} T_{ijt}\right) S_i \\ &\quad + \left(\beta_{0Z} + \beta_{XZ} X_{it} + \beta_{TZ} T_{ijt}\right) Z_i + \Delta\varepsilon_{ijt}. \end{aligned} \tag{12}$$

The coefficients in Equation (12) are identified since some workers change jobs, and for them we have $X_{it} > T_{ijt}$. We also note that the signs of the coefficients for the quadratic terms in Equation (11) are identical to those for the linear terms in Equation (12). Therefore, our test will utilize $\partial^3_{X^2Z} w = \beta_{XZ}$ and $\partial^3_{T^2Z} w = \beta_{TZ}$. First-differencing, however, cancels out the linear terms in Equation (11), and the test statistics proposed by Schönberg (2007) and Pinkston (2009) are not identified in Equation (12).[10]

In sum, our test of learning depends on two derivatives: $\partial^3_{X^2Z} w$ and $\partial^3_{T^2Z} w$. If learning is public (or symmetric, i.e., the information about the workers' productivity is perfectly transferred to outside firms), the wage growth path of the new job (net of individual-specific and job-match-specific effects, ω_{ij}) will be a continuation of the wage growth path of the previous job. This implies that $\partial^3_{X^2Z} w < 0$ and $\partial^3_{T^2Z} w = 0$. On the other hand, if learning is private (or asymmetric, i.e., no information about the workers' productivity is transferred to outside firms), the wage growth rate of the new job (net of individual-specific and job-match-specific effects, ω_{ij}) will be as steep as the wage growth path of the job after the initial labor market entry. This implies that $\partial^3_{X^2Z} w = 0$ and $\partial^3_{T^2Z} w < 0$. If learning is partially public

[9] This strategy has been adopted in the literature on returns to seniority. See, for example, Topel (1991).

[10] In a first-differenced model, the coefficients b_{X1Z} and b_{X1S} in Equation (11) are not separately identified.

(i.e., some but not all of the workers' information is transferred to outside firms), we expect both derivatives to be negative, $\partial^3_{X^2Z} w < 0$ and $\partial^3_{T^2Z} w < 0$. We test these predictions in Section 4.

3 Data and Descriptive Statistics

The analysis is based on the 1979-2000 waves of the National Longitudinal Survey of Youth 1979 (NLSY79). This survey is sponsored by the Bureau of Labor Statistics of the U.S. Department of Labor, which gathered information on a nationally representative sample of individuals living in the U.S. 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.

Our sample selection criteria follow Altonji and Pierret (2001). Specifically, we restrict the analysis to men who had completed eight or more years of education. We exclude labor market observations prior to the first time that an individual left school and accumulate experience from that point. We follow Pinkston (2009) in constructing the measure of actual work experience and tenure. Actual experience is the number of weeks in which the individual worked, and potential experience is constructed as years since the respondent first left school. 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 thus measured in years.

The Armed Forces Qualifying Test (AFQT) scores have been standardized by the age of the individual at the time of the test. As done in many studies, we consider the AFQT score as a variable that is correlated with a worker's ability, and which is observed by researchers but not by employers, whereas education is observed by both employers and researchers. When we analyze the wage changes, we further restrict the sample to individuals who do not change education between successive years.[11]

[11] To reduce the influence of measurement error and outliers, wage rates are set to missing when they are less than \$1 in 1982-84 dollars. For wage change specification, wages that are more than 800 percent or less

Table 1. Summary Statistics of Selected Variables

	Mean	SD
AFQT	0.0817	0.9571
Schooling	13.088	2.4571
Log of Real Wage	2.0396	0.5521
Actual Experience	8.4748	5.5721
Potential Experience	10.275	6.1179
Tenure	3.7536	4.1453

Table 1 presents summary statistics of selected variables in our sample. The average log hourly wage in 1982-84 dollars is 2.04. The average worker has completed 13.09 years of education. The worker's average potential experience is 10.28 years, his average actual experience is 8.47 years, and his average tenure is 3.75 years.

4 Estimation Results

We estimate the first-differenced model in Equation (12) for individuals who stay in the same job for two adjacent periods. The results of the analysis are presented in Table 2, column 1. The effect of AFQT on the curvature of the wage-experience profile (the coefficient on AFQT $\times$ experience) is -0.0023 (0.0063), and the effect of AFQT on the curvature of the wage-tenure profile (the coefficient on AFQT $\times$ tenure) is -0.0004 (0.0074). Although the coefficient on AFQT interacted with experience is more negative than that on AFQT interacted with tenure, we cannot draw a clear inference as to whether employer learning is public or private since neither of these coefficients is statistically significant.

than one-eighth of the previous year's value are dropped as well.

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

Dep. Variable: $\Delta \log wage$	All	All	High School Graduates	College Graduates
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0113**	0.0218**	0.0265**	-0.0107
	(0.0045)	(0.0076)	(0.0096)	(0.0290)
AFQT×Experience / 10	-0.0023	-0.0156	-0.0506*	0.1957**
	(0.0063)	(0.0217)	(0.0283)	(0.0849)
AFQT×Experience^2 / 100		0.0068	0.0235*	-0.1203**
		(0.0101)	(0.0135)	(0.0467)
AFQT×Tenure / 10	-0.0004	-0.0225	0.0075	-0.1195
	(0.0074)	(0.0228)	(0.0270)	(0.0932)
AFQT×Tenure^2 / 100		0.0128	-0.0033	0.0669
		(0.0122)	(0.0145)	(0.0564)
Schooling	0.0033*	0.0003		
	(0.0020)	(0.0036)		
Schooling×Experience / 10	-0.0032	0.0001		
	(0.0025)	(0.0086)		
Schooling×Experience^2 / 100		-0.0015		
		(0.0042)		
Schooling×Tenure / 10	0.0027	0.0089		
	(0.0032)	(0.0099)		
Schooling×Tenure^2 / 100		-0.0033		
		(0.0061)		
N	19915	19915	8621	3077

Note: White/Huber standard errors clustered at the individual level are in parentheses.
All specifications control for experience, tenure, and year effects. Columns (2)-(4) add controls for experience squared and tenure squared.
** Significant at the 5 percent level. * Significant at the 10 percent level.

We then allow for the AFQT score and schooling to have different effects on the change in log wages, depending on experience and tenure levels, by adding quadratic terms ($X_{it}^2 Z_i$, $X_{it}^2 S_i$, X_{it}^2, $T_{ijt}^2 Z_i$, $T_{ijt}^2 S_i$, and T_{ijt}^2) to the first-differenced model in Equation (12). Based on this quadratic specification, Table 2, column 2 reports the coefficient estimates. Using these estimates, the solid line in Panel A of Figure 2 shows $\partial^3_{X^2 Z} w$ by experience, i.e., the predicted effects of AFQT on the curvature of the wage-experience profile. The solid line in Panel B shows $\partial^3_{T^2 Z} w$ by tenure, i.e., the predicted effects of AFQT on the curvature of the wage-tenure profile. (The dashed lines in Panels A and B of Figure 2 indicate the 95 percent confidence interval of the predicted values.) Both the predicted effects of AFQT on the curvature of the wage-experience and wage-tenure profiles take values close to zero, and again we cannot draw a clear inference on the types of employer learning.

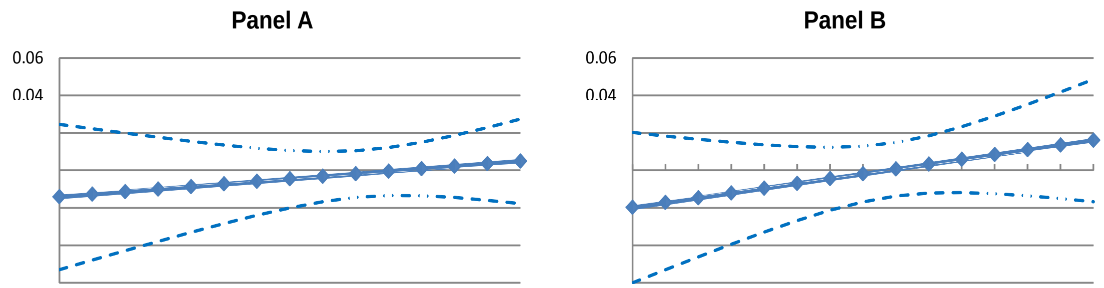

Figure 2. $\partial^3_{X^2 Z} w$ by Experience (Panel A), and $\partial^3_{T^2 Z} w$ by Tenure (Panel B): All Workers

Finally, since there may be differential AFQT effects of experience and tenure by worker's education, and since the return to education may also vary by worker's experience, we estimate the first-differenced model by two separate levels of education: high school graduates (12 years of education) and college graduates (16 years of education). Using the same specification as in Table 2, column 2, the results for high school graduates are presented in Table 2, column 3 and Figure 3; those for college graduates are in Table 2, column 4 and Figure 4. The effect of AFQT on the curvature of the wage-experience profile is negative until 10.75 years, while the effect of AFQT on the curvature of the wage-tenure profile is insignificantly small and takes values close to zero. Therefore, $\partial^3_{X^2 Z} w < 0$ and $\partial^3_{T^2 Z} w = 0$ for individuals during the first ten years of labor market experience, which provides evidence consistent with the public learning hypothesis. For college graduates, the effects of AFQT on the curvature of the wage-experience and wage-tenure profiles is positive until 8.13 years and becomes negative after that. The 95 percent confidence interval of the effect of AFQT on the curvature of the wage-tenure profile always contains values of zero. Therefore, for college graduates, learning is public after eight years of labor market experience, since $\partial^3_{X^2 Z} w < 0$ and $\partial^3_{T^2 Z} w = 0$.[12]

[12] To make a comparison with Schönberg (2007), we replicate her estimation results using our sample (see the results in Appendix, Table 1). We find that the impact of the AFQT score significantly increases with experience, but varies little with tenure. Similarly, the impact of schooling slightly decreases with experience,

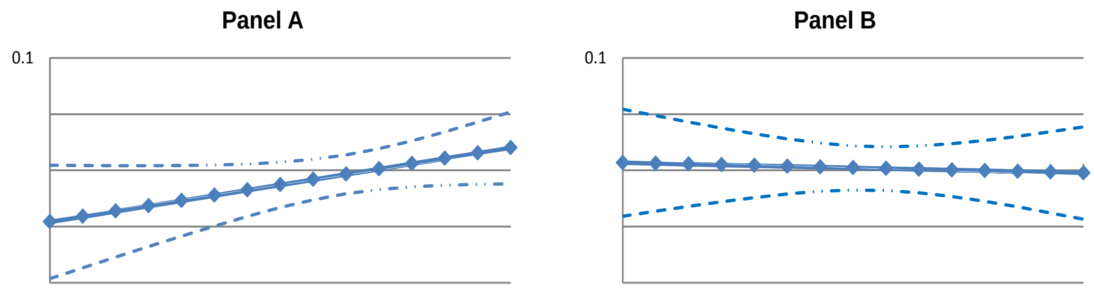

Figure 3. $\partial^3_{X^2Z}w$ by Experience (Panel A), and $\partial^3_{T^2Z}w$ by Tenure (Panel B): High School Graduates

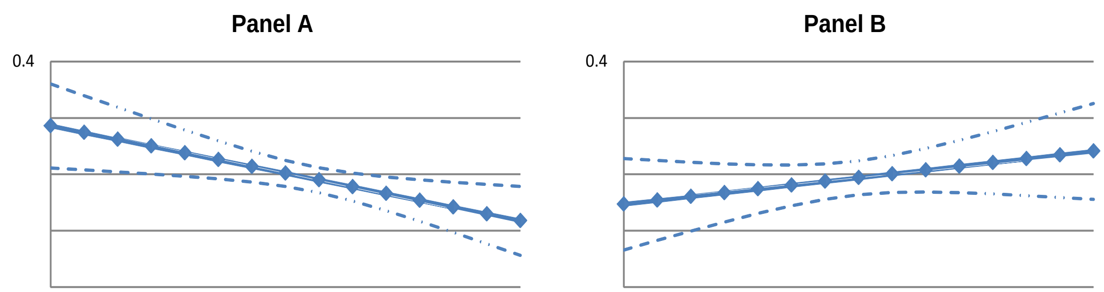

Figure 4. $\partial^3_{X^2Z}w$ by Experience (Panel A), and $\partial^3_{T^2Z}w$ by Tenure (Panel B): College Graduates

As we discussed in Section 2, an advantage of estimating the first-differenced model in Equation (12) is that the match-specific effect, ω_{ij}, cancels out, and thereby provides a consistent estimate for the quadratic terms in the wage-level model in Equation (11). However, the disadvantage is that the linear terms in the wage-level model in Equation (11) will not be identified.[13] To examine whether the signs of the linear terms in the wage-level

but changes little with tenure. The results for the sample restricted to high school graduates mirror those for all education groups. From this finding, Schönberg (2007) concludes that learning is symmetric for this group. On the other hand, for college graduates, the p-value of the joint significance of the coefficients on AFQT $\times$ experience and AFQT $\times$ experience squared is two times greater than that of the coefficients on AFQT $\times$ tenure and AFQT $\times$ tenure squared. This pattern is also found in Schönberg (2007), and she suggests that this offers support for the asymmetric learning hypothesis.

[13]Since the linear terms in the wage-level model in Equation (11) are not identified, we cannot conclude whether $\partial^3_{X^2Z}w = 0$ (or $\partial^3_{T^2Z}w = 0$) implies that the effect of AFQT does not increase with experience (or tenure) at all or the effect of AFQT increase with experience (or tenure) at a constant rate.

model in Equation (11) are in accordance with our predictions, we estimate the wage-level model by OLS and IV to obtain the linear terms (b_{X1Z} and b_{T1Z}), as shown in Appendix Table 1. Specifically, for the IV estimator, we use the estimator proposed by Altonji and Shakotko (1987), which instruments tenure with its deviations from job means and experience with its deviations from individual means. We then substitute these linear terms (i.e., b_{X1Z} and b_{T1Z}) and the estimates obtained from the first-differenced model in Equation (12) (i.e., β_{XZ} and β_{TZ}) into the linear term in Equation (11) that was not initially testable (i.e., $\partial^2_{XZ}w$ and $\partial^2_{TZ}w$). We find that $\partial^2_{XZ}w > 0$ and $\partial^2_{TZ}w = 0$, and therefore, the estimates from the linear model also support the public learning hypothesis (results not reported). In the next section, we use both the first-differenced model in Equation (12) and the linear terms in the wage-level model in Equation (11) to show that our findings are robust to alternative estimation strategies. Since the main contribution of our paper is to highlight the importance of examining the first-difference model, and since the linear terms in the wage-level model have already been examined by Schönberg (2007), we focus only on the former model in the next section, where we therefore explain the estimation results only from the first-differenced model in Equation (12).

In conclusion, the results in this section indicate that for high school graduates early in their career, but for college graduates later in their career, the wage growth paths in a new job are a continuation of the wage growth paths in the previous job. We therefore conclude that workers' information is perfectly transferred to outside firms for these groups of workers.

5 Robustness Checks

We next conduct several robustness checks to verify our findings that, in general, employer learning is public. Specifically, we further examine whether learning is different by workers' age. We also test whether our results are robust to dropping uncompleted job spells. In addition, we analyze the learning process for different occupational groups. Lastly, 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. The results are presented in Tables 3A and 3B.

First, the empirical results from Section 4 indicate that learning is public during the first ten years of labor market experience for high school graduates, but it is public only after eight years of labor market experience for college graduates. To further investigate whether this prediction is supported by alternative specifications, we test our learning hypothesis by estimating a linear first-differenced model in Equation (12) but separating the NLSY79 sample into individuals who are younger than age 30, and those who are 30 and older. For high school graduates who are younger than age 30, the coefficient on the AFQT $\times$ experience is -0.0304 (0.0209) and the coefficient on the AFQT $\times$ tenure is 0.0276 (0.0241), as shown in Table 3A, column 1. The F-test of whether these two coefficients are jointly equal to zero is 1.89 (p-value = 0.1698). For high school graduates who are age 30 and older, the coefficient on the AFQT $\times$ experience is 0.0336 (0.0164) and the coefficient on the AFQT $\times$ tenure is -0.0054 (0.0117), as shown in Table 3A, column 2. Therefore, the signs of the coefficients for high school graduates who are younger than age 30 are in accordance with the public learning hypothesis, but for high school graduates who are age 30 and older, the signs of the coefficients do not support public learning.

On the other hand, for college graduates who are younger than age 30, we cannot draw an inference about our learning hypothesis since the coefficient on the AFQT $\times$ experience is positive and that on the AFQT $\times$ tenure is close to zero. However, for college graduates age 30 and over, the coefficient on the AFQT $\times$ experience is -0.1070 (0.0393), which is significant at the 5 percent level, and the coefficient on the AFQT $\times$ tenure is -0.0073 (0.0344), which is close to zero; therefore, these results provide support for the public learning hypothesis. These results are in line with those obtained in Section 4.

Table 3A. Robustness Checks
Sample: Individuals who stay in the same job for two adjacent periods.

Dep. Variable: $\Delta \log wage$	High School Graduates		College Graduates	
	Under age 30	Age 30 and over	Under age 30	Age 30 and over
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0183**	-0.0373**	-0.0076	0.1325**
	(0.0087)	(0.0188)	(0.0285)	(0.0482)
AFQT×Experience / 10	-0.0304	0.0336**	0.0731	-0.1070**
	(0.0209)	(0.0164)	(0.0487)	(0.0393)
AFQT×Tenure / 10	0.0276	-0.0054	-0.0279	-0.0073
	(0.0241)	(0.0117)	(0.0596)	(0.0344)
N	5136	3485	1501	1576

Note: White/Huber standard errors clustered at the individual level are in parentheses.
All specifications control for actual experience, tenure, and year effects.
** Significant at the 5 percent level. * Significant at the 10 percent level.

Second, as discussed in Section 2.2, in the case of private learning, the sequence of wages converges to the sequence of the incumbent employer's expectations of a worker's productivity, and the speed of convergence decreases with job tenure. However, long-tenured employees may have a high job-match component ω_{ij}, which is hard to improve on; and therefore, incumbent employers who hire such workers will have fewer outside employers to compete with. In such a case, the gap between the incumbent employer's expectations of worker productivity and the realized wages may narrow more slowly. To examine the severity of this problem, we restrict our sample to completed job spells, and delete the censored job spells (i.e., job spells still in progress at the last survey date). For high school graduates, the effect of AFQT on the curvature of the wage-experience profile is significantly negative, and the effect of AFQT on the curvature of the wage-tenure profile takes values close to zero until ten years of labor market experience (see column 1, Table 3B; and Figure 5). For college graduates, the effect of AFQT on the curvature of the wage-experience profile is negative, and the effect of AFQT on the curvature of the wage-tenure profile takes values close to zero after nine years of labor market experience (see column 2, Table 3B; and Figure 6). Although not statistically significant, the coefficients on the AFQT interacted with experience, as well as on the AFQT interacted with experience squared, are more negative than those interacted with tenure, compared to the results in Table 2, columns 3 and 4. These results offer stronger evidence in support for the public learning hypothesis ($\partial^3_{X^2Z}w < 0$ and $\partial^3_{T^2Z}w = 0$).

Table 3B. Robustness Checks
Sample: Individuals who stay in the same job for two adjacent periods.

Dep. Variable: $\Delta \log wage$ Independent Variable:	Censored Job Spells Excluded: High School Graduates (1)	Censored Job Spells Excluded: College Graduates (2)	Service Group (3)	Managerial Group (4)
AFQT	0.0328**	-0.0528	0.0307**	0.0004
	(0.0140)	(0.0695)	(0.0134)	(0.0210)
AFQT×Experience / 10	-0.1027*	0.3406**	-0.0778**	0.0879**
	(0.0539)	(0.1541)	(0.0330)	(0.0448)
AFQT×Experience^2 / 100	0.0519*	-0.1997**	0.0380**	-0.0386**
	(0.0314)	(0.0957)	(0.0153)	(0.0187)
AFQT×Tenure / 10	0.0469	0.0017	0.0306	-0.1082**
	(0.0513)	(0.3195)	(0.0422)	(0.0516)
AFQT×Tenure^2 / 100	-0.0265	-0.1698	-0.0212	0.0575**
	(0.0333)	(0.3013)	(0.0243)	(0.0292)
Schooling			-0.0030	-0.0004
			(0.0065)	(0.0095)
Schooling×Experience / 10			0.0156	0.0001
			(0.0150)	(0.0196)
Schooling×Experience^2 / 100			-0.0080	-0.0049
			(0.0070)	(0.0094)
Schooling×Tenure / 10			-0.0031	0.0152
			(0.0173)	(0.0225)
Schooling×Tenure^2 / 100			0.0029	-0.0003
			(0.0097)	(0.0115)
N	4723	1522	7833	5047

Note: White/Huber standard errors clustered at the individual level are in parentheses.
All specifications control for experience, experience squared, tenure, tenure squared, and year effects.
** Significant at the 5 percent level. * Significant at the 10 percent level.

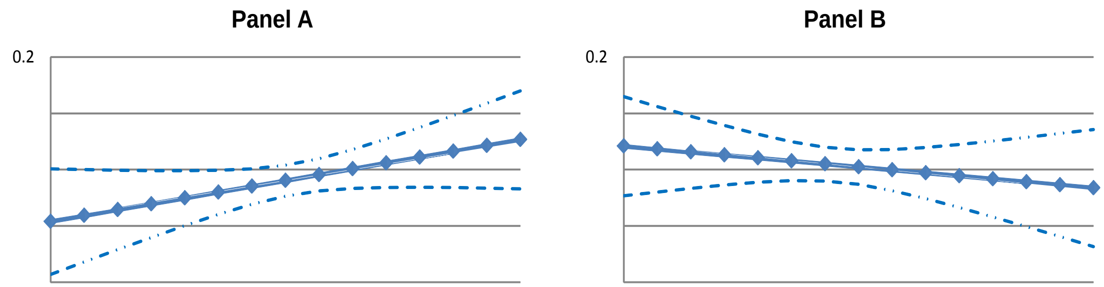

Figure 5. $\partial^3_{X^2Z}w$ (Panel A), and $\partial^3_{T^2Z}w$ (Panel B), Censored Job Spells Excluded: High School Graduates

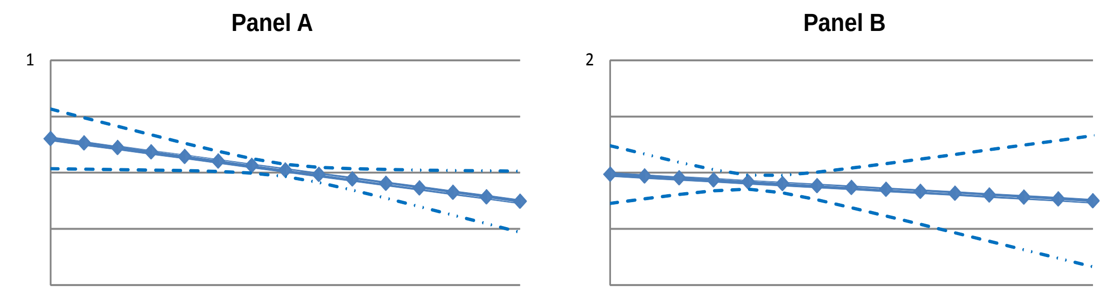

Figure 6. $\partial^3_{X^2Z}w$ (Panel A), and $\partial^3_{T^2Z}w$ (Panel B), Censored Job Spells Excluded: College Graduates

Third, whether the employer's private learning is transferred to outside firms may depend on the type of occupation an individual holds. For example, the productivity of service workers may be perfectly transferred to outside firms, but the productivity of managers may not be. That is, learning may be public for individuals in service occupations, but learning may be private for those in managerial occupations. To examine this issue, we divided the sample into two groups by occupation category at the one-digit level: (1) sales workers, clerical workers, operatives, laborers, and service workers (the so-called service group) and (2) managers and administrators, and craftsmen and foremen (the so-called managerial group). Since occasionally an individual's occupational category changes within a job even at the one-digit level,[14] we consider that the occupation category when the individual first started working for a particular employer is the occupation category throughout the time the individual stays with that particular employer. Column 3 in Table 3B and Figure 7 report the results for the service group. The effect of AFQT on the curvature of the wage-experience profile is significantly negative, and the effect of AFQT on the curvature of the wage-tenure profile takes values close to zero. For the managerial group, the results are reported in column 4 in Table 3B and in Figure 8. The effect of AFQT on the curvature of the wage-tenure profile is significantly negative, and the effect of AFQT on the curvature of the wage-experience profile is insignificant and positive. As predicted, learning is public for individuals who work in the service group, but private for those in the managerial group.

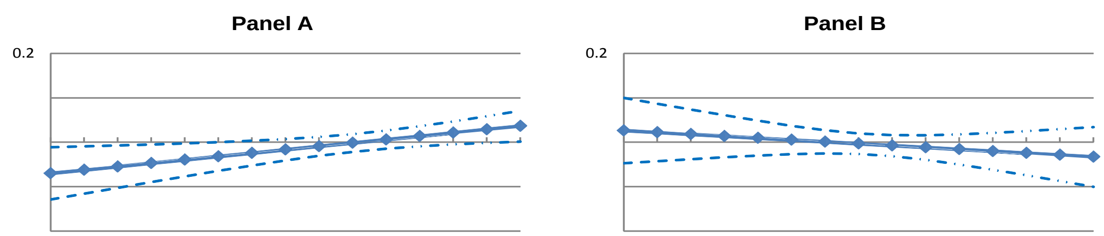

Figure 7. $\partial^3_{X^2Z}w$ by Experience (Panel A), and $\partial^3_{T^2Z}w$ by Tenure (Panel B): Service Group

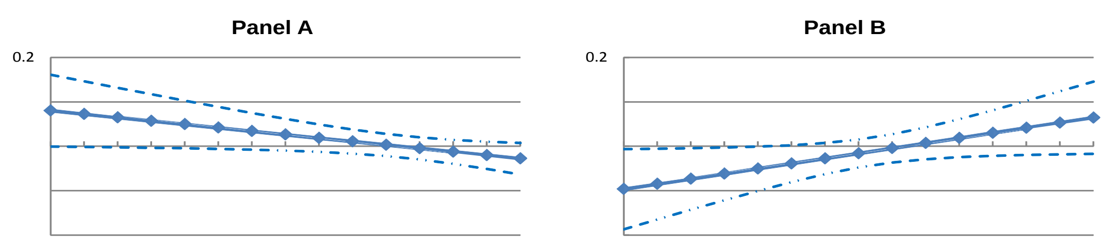

Figure 8. $\partial^3_{X^2Z}w$ by Experience (Panel A), and $\partial^3_{T^2Z}w$ by Tenure (Panel B): Managerial Group

Lastly, learning may be different depending on whether job change is induced by a quit

[14]According to Neal (1999), this is most likely due to reporting errors instead of actual changes in occupation.

or a layoff, because the reason the workers have left their previous jobs may have an effect on whether their new employers learn from those workers' past outcomes. For example, if a worker quits the previous job and moves to a new job, employer learning may be private. However, if a worker is laid off from the previous job, employer learning may be public (because layoffs signal that they are lemons, and all employers acquire this information). To see this point, we identify quits and layoffs, and estimate the first-differenced model separately for those who quit and for those who were laid off. We assign $Q_{ijt} = 1$ if job j started due to a quit from the previous job, and assign $L_{ijt} = 1$ if job j started due to a layoff from the previous job. We then estimate the following for individuals who stay in the same job for two adjacent periods, but separately for high school and college graduates:

$$\begin{aligned}
\Delta w_{ijt} &= \beta_0 + \beta_X X_{it} + \beta_{X2} X_{it}^2 + \beta_T T_{ijt} + \beta_{T2} T_{ijt}^2 \\
&\quad + \left(\beta_{0Q} + \beta_{XQ} X_{it} + \beta_{X2Q} X_{it}^2 + \beta_{TQ} T_{ijt} + \beta_{T2Q} T_{ijt}^2\right) Q_{ijt} \\
&\quad + \left(\beta_{0L} + \beta_{XL} X_{it} + \beta_{X2L} X_{it}^2 + \beta_{TL} T_{ijt} + \beta_{T2L} T_{ijt}^2\right) L_{ijt} \\
&\quad + \left(\beta_{0Z} + \beta_{XZ} X_{it} + \beta_{X2Z} X_{it}^2 + \beta_{TZ} T_{ijt} + \beta_{T2Z} T_{it}^2\right) Z_i \\
&\quad + \left(\beta_{0ZQ} + \beta_{XZQ} X_{it} + \beta_{X2ZQ} X_{it}^2 + \beta_{TZQ} T_{ijt} + \beta_{T2ZQ} T_{ijt}^2\right) Z_i Q_{ijt} \\
&\quad + \left(\beta_{0ZL} + \beta_{XZL} X_{it} + \beta_{X2ZL} X_{it}^2 + \beta_{TZL} T_{ijt} + \beta_{T2ZL} T_{ijt}^2\right) Z_i L_{ijt} + \Delta\varepsilon_{it}. \quad (13)
\end{aligned}$$

Due to space constraints, we provide the estimates on $\partial^3_{X^2 Z} w$ and $\partial^3_{T^2 Z} w$ for a specific year of labor market experience, chosen from the period in which we find evidence of public learning from the results in Section 4, namely, the second year of work experience for high school graduates, and the twelfth year of work experience for college graduates. In contrast to our earlier prediction, the estimates for quits are consistent with the public learning hypothesis, but we cannot draw a clear inference as to whether learning is public or private from the estimates for layoffs. For high school graduates with two years of labor market experience who work in jobs that started due to a quit from the previous job, the estimate on $\partial^3_{X^2 Z} w$ is -0.0628 (0.0384) and the estimate on $\partial^3_{T^2 Z} w$ is 0.0166 (0.0441). For college graduates with twelve years of labor market experience who work in jobs that started due to a quit from the previous job, the estimate on $\partial^3_{X^2Z}w$ is -0.1296 (0.0528) and the estimate on $\partial^3_{T^2Z}w$ is 0.0945 (0.0719). In contrast, for high school graduates whose jobs started due to a layoff from the previous job, the estimate on $\partial^3_{X^2Z}w$ is 0.0343 (0.0496) and the estimate on $\partial^3_{T^2Z}w$ is 0.0126 (0.0614), and for college graduates whose jobs started due to a layoff from the previous job, the estimate on $\partial^3_{X^2Z}w$ is 0.0753 (0.1456) and the estimate on $\partial^3_{T^2Z}w$ is -0.4262 (0.4758). The weak results for layoffs may be because the layoff sample in the NLSY79 include those displaced by layoffs and those displaced by plant closings, and so it is not possible to test for the lemons effect of layoff as in Gibbons and Katz (1991).[15]

Overall, the robustness checks support our main empirical findings from Section 4. At the same time, there is additional evidence that employer learning depends on occupation: it tends to be symmetric for service workers and operatives, but asymmetric for managerial occupations.

6 Concluding Remarks

This paper has taken a new approach to identifying the 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 be different depending on whether learning is public or private, and this will result in a difference in the amount of additional information that 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 job change and over the job tenure are related to the returns to experience and tenure. If employer learning is public, the wage growth paths in the new job

[15] After the year 1985, the layoff sample can be separated into those displaced by layoffs and those displaced by plant closings. The number of observations for layoffs are 758 (139) for high school (college) graduates; and for plant closings, they are only 143 (50) for high school (college) graduates. Although the estimates on $\partial^3_{X^2Z}w$ are more negative for layoffs than for plant closings, the estimates are noisy.

will be a continuation of the wage growth paths in the previous job. In contrast, if learning is private, the wage growth paths in the new job will be as steep as those in the first job at the time of labor market entry.

We test the implications produced by our theoretical model by using the sample of individuals who stay in the same job for two adjacent periods in the NLSY79. In general, the results are consistent with public learning. We find that the contribution to wages of the factors observed only by researchers, but not by employers (i.e., the AFQT score), increase at a decreasing rate with experience, but not with tenure. We also find evidence that employer learning about newly hired workers may depend on the type of occupation a worker holds: it tends to be public for service workers and operatives, but private for managerial occupations.

7 Appendix

Appendix Table 1. Effects of AFQT and Education by Experience and Tenure on Log Wages

Dep. Variable: $\log wage$	OLS	IV	OLS High School Graduates	OLS College Graduates
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0312**	0.0080	0.0245**	0.0159
	(0.0082)	(0.0209)	(0.0108)	(0.0410)
AFQT×Experience / 10	0.0728**	0.3470**	0.0636*	0.0873
	(0.0267)	(0.0781)	(0.0372)	(0.1231)
AFQT×Experience^2 / 100	-0.0309**	-0.1431**	-0.0211	0.0160
	(0.0131)	(0.0336)	(0.0177)	(0.0599)
AFQT×Tenure / 10	0.0132	-0.4027*	-0.0080	0.1195
	(0.0362)	(0.2213)	(0.0493)	(0.1507)
AFQT×Tenure^2 / 100	0.0126	0.2267*	0.0229	-0.1049
	(0.0215)	(0.1255)	(0.0270)	(0.0967)
Schooling	0.0433**	0.0282*		
	(0.0054)	(0.0170)		
Schooling×Experience / 10	-0.0310**	-0.0105		
	(0.0154)	(0.0508)		
Schooling×Experience^2 / 100	0.0051	-0.0077		
	(0.0079)	(0.0215)		
Schooling×Tenure / 10	0.0108	0.1339		
	(0.0164)	(0.0907)		
Schooling×Tenure^2 / 100	-0.0043	-0.0602		
	(0.0112)	(0.0549)		
N	36236	36236	14615	4853

Note: White/Huber standard errors clustered at the individual level are in parentheses.
All specifications control for occupation and industry, schooling, year dummies, year dummies interacted with schooling, actual experience and its square, and tenure and its square.
** Significant at the 5 percent level. * Significant at the 10 percent level.

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