Employer Learning, Job Mobility, 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 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 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 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 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.

[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.

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 for high school graduates. 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 for high school graduates. In contrast, we find that the contribution to wages of the factors observed only by researchers increases at a decreasing rate with tenure but not with experience for college graduates. Therefore, learning is private for college graduates.

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 elements 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]

We make several assumptions on the fixed unobserved heterogeneity, ω_{ij} and η_i, in Equation (1). First, ω_{ij} is time-invariant within an employment relationship, and is the expectation of $\omega_{ij} + \eta_i$ conditional on employer j's information set. In general ω_{ij} is non-zero because employer j uses public as well as private information to evaluate the productivity of worker i. This value is unknown to the researcher, but is known to the employer at the beginning of an employment relationship. This value is different for outside employers as they offer different jobs and have different information sets. Second, η_i is fixed throughout an individual's career,

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

and this is what employers learn about. While η_i is unknown to employers, we assume that η_i is a normal random variable with expectation zero and variance σ_η^2, and this distributional assumption is common to all employers. To employers, η_i is the prediction error of $\omega_{ij} + \eta_i$, but researchers who have access to data may have partial information about η_i. It is possible that two workers with identical ω_{ij} who are observationally equivalent conditional on the initial information set may possess different η_i.

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 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

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

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. The signal which the new employer j' receives from applicant i about η_i at the time of the job change, $\overrightarrow{s}_{ij}$, may include worker i's last wage with the previous employer j, regardless of whether learning is symmetric or not. The signal, $\overrightarrow{s}_{ij}$, may also include the information that whether the job change was due to quit or layoff.

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

[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.

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

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

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

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

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).[5]

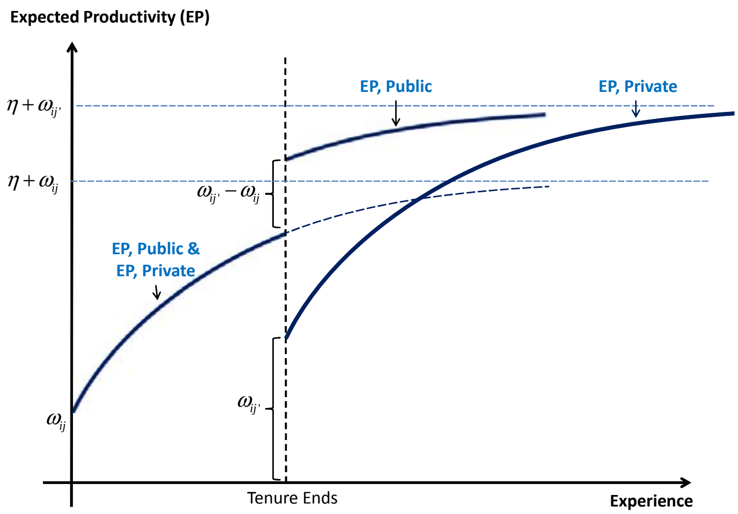

Figure 1A: Expected Productivity when $f(H_{ijt}) = 0$.

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.

[5]It is important to note that this prediction holds even if job changes are endogenous. For example, quits and layoff may send different messages to new employers by affecting $\overrightarrow{s}_{ij}$. However, for any given $\overrightarrow{s}_{ij}$, the wage dynamics after a job change will be explained (7), (8), (9), and (10).

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. In this discussion, we follow the convention in this literature that all wage contracts are spot and exclude the possibility of a long-term contracts.[6]

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.[7] 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, $f(H_{ij,t+1}) - f(H_{ijt})$. If the worker decides to stay in his/her current job in the next period, the gap between the current employer's 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

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

[7] This logic holds whether or not ω_{ij} is included in the model. However, the logic may not hold if many workers have gone trough periods of more than one year without receiving an offer. In reality, unemployment duration is not that long in the United States. In the CPS from 1981 to 2002, the average unemployment duration for men is 16.9 weeks = 4.225 months according to Mukoyama and Sahin (2008). Among men who are laid off in the 1979-2000 waves of the NLSY79, 81.7 percent move to new jobs within 12 months (whereas for quits, it is 88.2 percent). It appears that layoffs receive at least one job offer within a year, but they only accept the offer when it is greater than their reservation wage.

paths to decrease with job tenure, which is our key testing strategy. However, this follows straightforwardly from Pinkston's (2009) result. In our model, the sequence of wages converges to the sequence of the incumbent employer's expectation of the worker's productivity due to outside offers. 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.

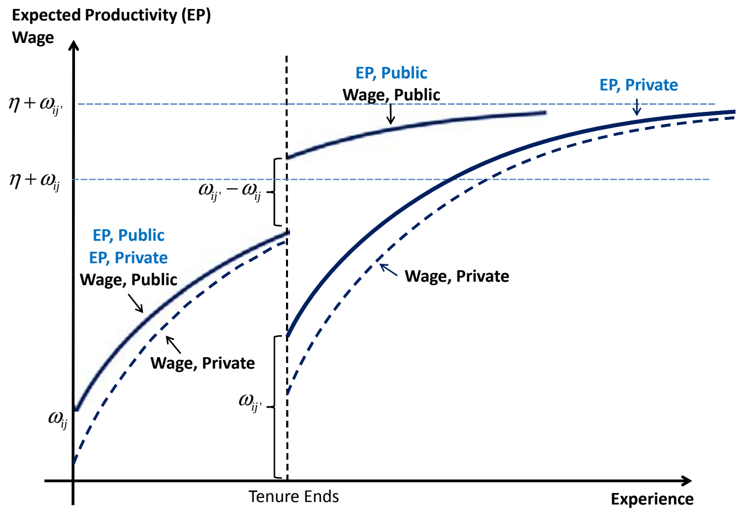

Figure 1B: Expected Productivity and Wages when $f\left(H_{ijt}\right) = 0$.

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:

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

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 $\partial^2_{XS}w = b_{X1S} + 2b_{X2S}X_{it} < 0$.[8]

Schönberg (2007) and Pinkston (2009) extend this framework to test for the type of employer learning.[9] 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 $\partial^2_{XZ}w = \partial^2_{XS}w = 0$.[10] 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 vary over time. We also adopt this convention of focusing on Z_i.

While it is an interesting idea to include tenure (or employment spell length) in addition to experience to test the type of learning, the literature on tenure is specifically concerned about including tenure in a wage equation. According to Topel (1991), both the coefficient on experience and tenure will be inconsistent due to endogenous job changes. Therefore, any interpretation based on the OLS coefficient estimates on experience and tenure will be misleading. He proposes first-differencing, but it does not function with Schönberg or Pinkston as the linear terms will collapse into an intercept in a first differenced model.

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,

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

[9] 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.

[10] 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.

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 both sets of coefficients on experience and tenure 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.[11] 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 additional 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:[12]

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

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

[11] 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.

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

Pinkston (2009) are not identified in Equation (12).[13]

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 (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.

An important assumption commonly made in this literature is that the deterministic wage growth path is perfectly captured by experience, tenure, and education controls. In practice, however, workers with higher Z_i may also have steeper wage growth. Then, an estimate of $\partial^3_{X^2Z}w$ or $\partial^3_{T^2Z}w$ will reflect the effects of employer learning as well as the differential wage growth path for different level of Z_i. Since higher Z_i is associated with faster wage growth, the estimate of $\partial^3_{X^2Z}w$ or $\partial^3_{T^2Z}w$ will serve as an upper limit of employer learning. Therefore, 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 $\partial^3_{T^2Z}w$ would function as a strong evidence of public or private learning.

3 Data and Descriptive Statistics

The analysis is based on the 1979-2010 waves of the 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 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.

In selecting the sample, we refer to the sample selection criteria used in Altonji and Pierret (2001), Lange (2007), Pinkston (2009) and Arcidiacono, Bayer, and Hizmo (2010). We restrict the analysis to white men who had completed 12 or 16 years of education. We exclude

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

labor market activities prior to the first time that an individual left school and accumulate experience from that point. Potential experience is constructed as years 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. Actual experience and tenure are divided by 50, and thus measured in years. We follow Arcidiacono, Bayer, and Hizmo (2010) and Mansour (2012) to restrict the sample to observations where potential experience is less than 13 years.[14] When we analyze the wage changes, we further restrict the sample to individuals who do not change education between successive years. 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 than one-eighth of the previous year's value are dropped as well.

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.

Table 1A. Summary Statistics for High School and College Graduates

	High School Graduate		College Graduate	
	Mean	SD	Mean	SD
Normalized AFQT	-0.1107	0.8187	0.8648	0.5144
Real Hourly Wage	8.2362	4.7669	12.323	8.9283
Log of Real Hourly Wage	1.9998	0.4591	2.3730	0.5104
Potential Experience	6.8728	3.6288	6.2592	3.6305
Actual Experience	5.5549	3.3819	5.6189	3.4670
Tenure	2.7840	2.7792	3.1048	2.9325

Notes: Wages are in 1982-84 dollars. Experience and tenure variables are measured in years. There are 10,493 observations for high school graduates and 4,018 observations for college graduates.

Table 1A reports summary statistics in our sample for high school and collage graduates. The average log hourly wage in 1982-84 dollars is 1.9998 for high school graduates and 2.3730 for college graduates. For high school graduates, the worker's average potential experience is 6.8728 years, his average actual experience is 5.5549 years, and his average tenure is 2.7840 years. For college graduates, the worker's average potential experience is 6.2592 years, his

[14] Arcidiacono, Bayer, and Hizmo (2010) focuses on this experience interval for two reasons. First, the relationship between log wages, AFQT score, and potential experience is approximately linear in this experience interval, and so they can keep the analysis simple. Second, attrition increases noticeably with experience in the NLSY79.

average actual experience is 5.6189 years, and his average tenure is 3.1048 years. Relative to high school graduates, college graduates have higher average AFQT score, greater actual experience and tenure; and they earn higher wages.

Table 1B. Summary Statistics for High School and College Graduates by Job Mobility

	High School Graduates			
	Job Stayers		Job Movers	
	Mean	SD	Mean	SD
Normalized AFQT	-0.1010	0.8221	-0.1173	0.8051
Real Hourly Wage	8.9503	3.9590	7.2803	3.9462
Log of Real Wage	2.1058	0.4171	1.8818	0.4420
Change in Log of Real Wage	0.0450	0.2580	0.0374	0.4477
Potential Experience	7.7832	3.2595	6.7512	3.3839
Actual Experience	6.6255	3.0816	5.1047	3.0110
Tenure	4.2310	2.7152	0.5882	0.6521

	College Graduates			
	Job Stayers		Job Movers	
	Mean	SD	Mean	SD
Normalized AFQT	0.8746	0.5077	0.8275	0.5285
Real Hourly Wage	12.951	6.4389	11.046	5.7182
Log of Real Wage	2.4601	0.4502	2.2775	0.5060
Change in Log of Real Wage	0.0610	0.2610	0.0838	0.4705
Potential Experience	7.0500	3.3113	5.8322	3.4837
Actual Experience	6.5070	3.1865	5.0235	3.2220
Tenure	4.3822	2.8387	0.6409	0.6631

Notes: Experience and tenure variables are measured in years. For high school graduates, there are 5,681 observations for job stayers and 2,595 observations for job movers. For college graduates, there are 2,484 observations for job stayers and 777 observations for job movers.

Next, in Table 1B, we present summary statistics separately by job mobility to highlight the differences in characteristics between job stayers and job movers, since the first-differenced model in Equation (12) that we estimate is restricted to sample of job stayers, that is, individuals who work in the same job for two adjacent periods. For both high school and college graduates, job stayers have slightly higher AFQT score, have longer experience, and have accumulated about 4 years of seniority. On the other hand, average tenure for job movers is 0.5882 for high school graduates and 0.6409 for college graduates. For college graduates, the gain in log wages is 0.0838 for job movers and 0.0610 for job stayers, and thus the wage gain is greater for job movers than for job stayers perhaps because the gain in job-match specific error component is large for job movers.

4 Estimation Results

Many papers have pooled all 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). However, Arcidiacono, Bayer, and Hizmo (2010) show that pooling all education levels in wage regressions lead to biases and the misinterpretation of the results. In particular, they find significant statistical and economical differences between the college and the high school samples in the coefficients on AFQT and AFQT $\times$ experience when estimating the wage level model in Equation (11) that does not include the tenure terms. Specifically, for high school graduates, they find that the coefficient on AFQT is very small and statistically insignificant, but the coefficient on AFQT interacted with experience is positive and significant. In contrast, for college graduates, the coefficient on AFQT is large and statistically significant, while the coefficient on AFQT $\times$ experience is small and statistically insignificant. As a result, Arcidiacono, Bayer, and Hizmo (2010) conclude that employers learn slowly about the ability of high school graduates, while the ability of college graduates is directly revealed upon entry into the labor market. Schönberg (2007) also finds differences between the college and the high school samples when estimating the wage level model in Equation (11). She finds that the effect of the AFQT score on wages increases with experience but varies little with tenure for high school graduates, but the effect of the AFQT score rises with tenure up to the fifth year in the job for college graduates. Her study concludes that learning is largely symmetric for high school graduates, but the results for college graduates is potentially consistent with a model of asymmetric employer learning.

To fill the gap between these studies, we perform our estimation by two separate levels of education: high school graduates (12 years of education) and college graduates (16 years of education). The results for high school graduates that use potential experience as the experience measure are presented in specification (1) of Table 2, and those that use actual experience are presented in specification (2) of Table 2. In specification (1) of Table 2, the coefficient on AFQT $\times$ potential experience is -0.0321 (0.0146), and the coefficient on AFQT $\times$ tenure is 0.0192 (0.0161). In specification (2) of Table 2, the coefficient on AFQT $\times$ actual experience is -0.0299 (0.0178), and the coefficient on AFQT $\times$ tenure is 0.0215 (0.0190). Results from specifications (1) and (2) imply that $\partial^3_{X^2Z}w$ is negative and statistically significant, while $\partial^3_{T^2Z}w$ is small positive and statistically insignificant. Therefore, we find evidence consistent with the public learning hypothesis for high school graduates. These results are in line with Figure 3, Panel C of Arcidiacono et al. (2010) where they find a concave learning curve, even after accounting for the effect of the increasing productivity of AFQT. Our results are also in accordance with Schönberg (2007).

Specifications (3) and (4) of Table 2 repeat the same empirical analyses for college graduates. In specification (3) of Table 2, the coefficient on AFQT $\times$ potential experience is 0.789 (0.0310), and the coefficient on AFQT $\times$ tenure is -0.0906 (0.0404). In specification (4) of Table 2, the coefficient on AFQT $\times$ actual experience is 0.0691 (0.0370) and the coefficient on AFQT $\times$ tenure is -0.0870 $(0, 0433)$. Results from these specifications imply that $\partial^3_{T^2Z}w$ is negative and statistically significant, while $\partial^3_{X^2Z}w$ is positive and statistically significant. As we have discussed in Section 2, while it is possible to obtain a positive estimate of $\partial^3_{X^2Z}w$, the negative estimate of $\partial^3_{T^2Z}w$ suggest that learning is private for college graduates.[15]

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

Dep. Variable: $\Delta \log wage$	High School		College	
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0253**	0.0189**	0.0055	0.0136
	(0.0085)	(0.0078)	(0.0198)	(0.0201)
AFQT× Potential Experience / 10	-0.0321**		0.0789**	
	(0.0146)		(0.0310)	
AFQT× Actual Experience / 10		-0.0299*		0.0691*
		(0.0178)		(0.0370)
AFQT×Tenure / 10	0.0192	0.0215	-0.0906**	-0.0870**
	(0.0161)	(0.0190)	(0.0404)	(0.0433)
N	5681	5681	2484	2484

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

As discussed in Section 2, an advantage of estimating the within-job first differenced model in Equation (12) is that the individual-specific and match-specific effects η_i and ω_{ij} cancel 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.[16] To examine whether the signs of the linear terms

[15] To make a comparison with Schönberg (2007), we replicate her estimation results using our sample (see the results in Appendix, Table 1). For high school graduates, the effect of the AFQT score significantly increases with experience, but varies little with tenure. From this finding, Schönberg (2007) concludes that learning is symmetric. 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 70.9 percent and that of the coefficients on AFQT $\times$ tenure and AFQT $\times$ tenure squared is 5.1 percent. This pattern is also found in Schönberg (2007), and she suggests that this offers support for the asymmetric learning hypothesis.

[16] Since the linear terms in the wage-level model in Equation (11) are not identified, we cannot conclude

in the wage-level model in Equation (11) are in accordance with our predictions, we estimate the wage-level model to obtain the linear terms (b_{X1Z} and b_{T1Z}), as shown in Appendix Table 1. We find that $\partial^2_{XZ}w > 0$ and $\partial^2_{TZ}w = 0$ for high school graduates and $\partial^2_{XZ}w = 0$ and $\partial^2_{TZ}w > 0$ for college graduates; therefore, the estimates from the linear model also support the public learning hypothesis for high school graduates and private learning hypothesis for college graduates. Since the main contribution of our paper is to highlight the importance of examining the within-job 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 within-job first-differenced model in Equation (12).

5 Robustness Checks

In this Section, we conduct several robustness checks. First, we verify our findings that, employer learning is public for high school graduates and private for college graduates. Next, we examine whether the learning process differ by 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.

Pinkston (2009) presents a theoretical model that shows that private learning of employers will be reflected in wages over spells of continuous employment. This is because the bidding war would effectively transmit all of the incumbent employer's information to the new employer, even though the new employer did not observe the worker's performance in each period on the previous job. Since we introduce a match-specific component to productivity, wages will converge to the employer's private expectation over tenure instead of employment spell as in Pinkston (2009). As a robustness check, we examine whether there is a possibility of employer's private learning over spells continuous employment. Table 3A presents estimates of the within-job first difference model in Equation (12) that replaces tenure with spells of continuous employment. The results for high school graduates that use potential experience as the experience measure are presented in specification (1) of Table 3A, and those that use actual experience are presented in specification (2) of Table 3A. In specification (1) of Table 3A, the coefficient on AFQT × potential experience is -0.0431 (0.0176), and the coefficient

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.

on AFQT $\times$ spell length is 0.0347 (0.0179). In specification (2) of Table 3A, the coefficient on AFQT $\times$ actual experience is -0.0619 (0.0272), and the coefficient on AFQT $\times$ spell length is 0.0561 (0.0268). The estimate of $\partial^3_{X^2Z}w$ takes a statistically significant negative value and the estimate of $\partial^3_{T^2Z}w$ takes a positive value. Therefore, learning is public for high school graduates. For college graduates, the coefficient on AFQT $\times$ potential experience is 0.705 (0.0362), and the coefficient on AFQT $\times$ spell length is -0.0485 (0.0416) in specification (3) of Table 3A. The coefficient on AFQT $\times$ actual experience is 0.0400 (0.0446) and the coefficient on AFQT $\times$ spell length is -0.0253 (0.0455) in specification (4) of Table 3A. The estimate of $\partial^3_{T^2Z}w$ is statistically insignificant, but its sign is in accordance with the private learning hypothesis.

Table 3A. The Effects of AFQT on Change in Log Wages by Education
Sample: Individuals who stay in the same job for two adjacent periods.

Dep. Variable: $\Delta \log wage$	High School		College	
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0248**	0.0204**	-0.0015	0.0080
	(0.0084)	(0.0077)	(0.0198)	(0.0199)
AFQT×Potential. Experience / 10	-0.0431**		0.0705*	
	(0.0176)		(0.0362)	
AFQT×Actual Experience / 10		-0.0619**		0.0400
		(0.0272)		(0.0446)
AFQT×Spell Length / 10	0.0347*	0.0561**	-0.0485	-0.0253
	(0.0179)	(0.0268)	(0.0416)	(0.0455)
N	5714	5714	2489	2489

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

Next, we examine whether the learning process differ by occupational groups, since recently Mansour (2012) examines whether employer learning varies by initial occupation. In the wage-level model, he finds that the coefficient on AFQT is small and grows significantly with experience in occupations with high growth in the variance of residual wages, but the coefficient on AFQT is large and does not grow over time in occupations with low growth in the variance of residual wages. He concludes that there is significant heterogeneity in the employer learning process across occupations and that occupational assignment affects the learning process independently of education. As done in Table 3 of Mansour (2012), we classify the worker's initial occupation into three different groups: the upper, middle, and lower tercile of the growth in the variance residual of wage distribution. We then estimate the within-job first difference model for these three different groups of initial occupations. The results are reported in Table 3B. For high school graduates whose initial occupations had low growth in the residual variance ("low learning" occupations), there is evidence of public learning. Note that the coefficient on AFQT is positive and significant at the 5 percent level for the "low learning" occupations in the within-job first-difference model. For college graduates whose initial occupations had low or mid-growth in the residual variance ("low and mid-learning" occupations), there is evidence of private learning. In contrast to the results of Mansour (2012), employer learning takes place in "low and mid-learning" occupations, and whether the learning process is public or private differs by education.

Table 3B. The Effects of AFQT on Change in Log Wages by Group of Occupations
Sample: Individuals who stay in the same job for two adjacent periods.

Dep. Variable: $\Delta \log wage$	High School			College		
	Low	Mid	High	Low	Mid	High
Independent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
AFQT	0.0372*	0.0209	0.0248	-0.0150	0.0623	0.0424
	(0.0224)	(0.0212)	(0.0210)	(0.0258)	(0.0527)	(0.0418)
AFQT×Experience / 10	-0.0743**	0.0143	-0.0278	0.1207**	0.1255*	-0.1030
	(0.0374)	(0.0288)	(0.0421)	(0.0534)	(0.0693)	(0.0708)
AFQT×Tenure / 10	0.0660*	-0.0300	-0.0054	-0.0880*	-0.2870**	0.0776
	(0.0379)	(0.0333)	(0.0400)	(0.0503)	(0.1050)	(0.0813)
N	1118	1149	798	1065	502	837

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

Since occupations with low growth in the residual variance are mostly sales, service and clerical jobs, whereas occupations with mid-growth in the residual variance consist of managerial occupations and craftsmen (see Table 1 of Mansour (2012)), the employer learning process may vary by occupations due to the nature of occupation. For example, the productivity of service workers may be perfectly transferred to outside firms and thus learning may be public; but the productivity of managers may not be and thus learning may be private. To examine this issue, we estimate the within-job first difference model by education and 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,[17] 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. For high school graduates who work in the service group, the estimate of $\partial^3_{X^2 Z} w$ is significantly

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

negative, and the estimate of $\partial^3_{T^2Z}w$ takes values close to zero (specification (1) of Table 3C). Therefore, learning is public for these workers. However, for high graduates who work in the managerial group, the estimate of $\partial^3_{T^2Z}w$ is negative but insignificant (specification (2) of Table 3C). Similarly, for college graduates, regardless of occupation, the estimate of $\partial^3_{T^2Z}w$ is negative but insignificant. Therefore, we only find weak evidence in support of private learning for these workers.

Table 3C. The Effects of AFQT on Change in Log Wages by Group of Occupations
Sample: Individuals who stay in the same job for two adjacent periods.

Dep. Variable: $\Delta \log wage$	High School		College	
	Service	Managerial	Service	Managerial
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0284**	-0.0022	0.0493	0.0515
	(0.0091)	(0.0155)	(0.0363)	(0.0590)
AFQT×Experience / 10	-0.0402*	0.0137	0.0241	0.0504
	(0.0225)	(0.0251)	(0.0665)	(0.0595)
AFQT×Tenure / 10	0.0218	-0.0073	-0.0565	-0.1935
	(0.0245)	(0.0272)	(0.0836)	(0.1383)
N	3670	1744	969	518

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

Following Acemoglu and Autor (2011), we use O*NET task measures that are composite measures of O*NET Work Activities and Work Context Importance scales. Specifically, the O*NET task measures classified as: (1) Non-routine cognitive: Analytical, (2) Non-routine cognitive: Interpersonal, (3) Routine cognitive, (4) Routine manual, (5) Non-routine manual: Physical adaptability, (6) Non-routine manual: Interpersonal adaptability, and (7) Communication with persons outside organization.[18] Similar to Kahn (2013), we use the O*NET 4.0 (available in 2002), which is the earliest version of O*NET that more closely matches the sample period of NLSY79. We classify the sample into three groups (the upper, middle, and lower tercile) based on the respondents' O*NET task measures in the task distribution in 1970, and then estimate the within-job first difference model separately by task groups. For college graduates, we find that learning is private in occupations that require more Non-routine Cognitive: Analytical, Non-routine Cognitive: Interpersonal, and Non-routine Manual: Interpersonal Adaptability. For college graduates, we also find that learning is private in occupations that require less Routine Cognitive, and Non-routine Manual: Physical Adaptability.

[18] Acemoglu and Autor (2011) argue that managerial, professional, and technical occupations are specialized in abstract, non-routine cognitive tasks; clerical, administrative and sales occupations are specialized in routine cognitive tasks; production and operative occupations are specialized in routine manual tasks; and service occupations are specialized in non-routine manual tasks.

On the other hand, for high school graduates, we find that learning is public in occupations that require less Non-routine Cognitive: Analytical, and Non-routine Manual: Interpersonal Adaptability. It appears that for college graduates who work in jobs that require non-routine tasks, information about their ability is not transferred to outside firms. For high school graduates who work in jobs that require less of non-routine tasks, information about their ability is perfectly transferred to outside firms.

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

$$\begin{aligned}
\Delta w_{ijt} &= \beta_0 + \beta_{0Q} Q_{ijt} + \left(\beta_{XQ} X_{it} + \beta_{X2Q} X_{it}^2 + \beta_{TQ} T_{ijt} + \beta_{T2Q} T_{it}^2\right) Q_{ijt} \\
&\quad + \left(\beta_{XL} X_{it} + \beta_{X2L} X_{it}^2 + \beta_{TL} T_{ijt} + \beta_{T2L} T_{it}^2\right) L_{ijt} \\
&\quad + \left(\beta_{0ZQ} + \beta_{XZQ} X_{it} + \beta_{TZQ} T_{ijt}\right) Z_i Q_{ijt} \\
&\quad + \left(\beta_{0ZL} + \beta_{XZL} X_{it} + \beta_{TZL} T_{ijt}\right) Z_i L_{ijt} + \Delta\varepsilon_{it}. \qquad (13)
\end{aligned}$$

For high school graduates who work in jobs that started due to a quit from the previous job, the estimate on $\partial^3_{X^2Z} w$ is -0.0399 (0.0258) and the estimate on $\partial^3_{T^2Z} w$ is 0.0434 (0.0330); for those whose jobs started due to a layoff from the previous job, the estimate on $\partial^3_{X^2Z} w$ is -0.0536 (0.0371) and the estimate on $\partial^3_{T^2Z} w$ is 0.1063 (0.0411). For high school graduates, the estimates for both quits and layoffs are consistent with the public learning hypothesis.

For college graduates who work in jobs that started due to a quit from the previous job, the estimate on $\partial^3_{X^2Z} w$ is 0.1240 (0.0414) and the estimate on $\partial^3_{T^2Z} w$ is -0.0883 (0.0544). In contrast, for college graduates whose jobs started due to a layoff from the previous job, the estimate on $\partial^3_{X^2Z} w$ is -0.0615 (0.0918) and the estimate on $\partial^3_{T^2Z} w$ is 0.0196 (0.0891). For college graduates, our results provide weak evidence in support of our earlier prediction, that is, for a worker quits the previous job and moves to a new job, employer learning is private;

but if a worker is laid off from the previous job, employer learning is public. 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). After the year 1985, the layoff sample can be separated into those displaced by layoffs and those displaced by plant closings. In the college graduate sample, for quits, the estimate on $\partial^3_{X^2Z}w$ is 0.1262 (0.0449) and the estimate on $\partial^3_{T^2Z}w$ is -0.1504 (0.0431); for layoffs, the estimate on $\partial^3_{X^2Z}w$ is -0.0460 (0.1604) and the estimate on $\partial^3_{T^2Z}w$ is 0.1045 (0.2055); and for plant closing, the estimate on $\partial^3_{X^2Z}w$ is 0.7699 (0.2877) and the estimate on $\partial^3_{T^2Z}w$ is -0.8200 (0.4547).[19] Although the differences in estimates are not significant, the estimated signs indicate public learning for layoffs and private learning for quits and plant closings.

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 high school graduates in service workers and operatives, but asymmetric for college graduates who work in jobs that require non-routine tasks.

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 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. Our results

[19] For college graduates, the number of observations are 81 for layoffs and 23 for plant closings.

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 the factors observed only by researchers, but not by employers (i.e., the AFQT score), increases at a decreasing rate with experience, but not with tenure. Therefore, the wage growth paths in a new job are a continuation of the wage growth paths in the previous job, and so the workers' information is perfectly transferred to outside firms for high school graduates. In contrast, for college graduates, the contribution to wages of the factors observed only by researchers, but not by employers, increases at a decreasing rate with tenure, but not with experience. Thus, the wage growth paths in the new job will become closer to those in the first job at the time of labor market entry, and so the workers' information is not transferred to outside firms for college graduates.

Appendix

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

Dep. Variable: log *wage*	High School			
	OLS		IV	
Independent Variable:	(1)	(2)	(3)	(4)
AFQT	0.0077	0.0104	0.0068	0.0050
	(0.0126)	(0.0162)	(0.0117)	(0.0153)
AFQT×Pot. Experience / 10	0.0806**	0.0265		
	(0.0174)	(0.0601)		
AFQT×Pot. Experience^2 / 100		0.0310		
		(0.0450)		
AFQT×Actual Experience / 10			0.1202**	0.1532
			(0.0491)	(0.1422)
AFQT×Actual Experience^2 / 100				-0.0331
				(0.1241)
AFQT×Tenure / 10		0.0885	-0.0510	-0.0913
		(0.0748)	(0.0968)	(0.2312)
AFQT×Tenure^2 / 100		-0.0689		0.0445
		(0.0740)		(0.2402)
N	10168	10168	10168	10168

Dep. Variable: log *wage*	College			
	OLS		IV	
Independent Variable:	(5)	(6)	(7)	(8)
AFQT	0.0753*	0.0484	0.0608	0.0246
	(0.0402)	(0.0524)	(0.1316)	(0.0536)
AFQT×Pot. Experience / 10	0.0706	-0.0507		
	(0.0548)	(0.2103)		
AFQT×Pot. Experience^2 / 100		0.0843		
		(0.1495)		
AFQT×Actual Experience / 10			-0.0494	-0.5780
			(0.1316)	(0.3796)
AFQT×Actual Experience^2 / 100				0.5613*
				(0.3150)
AFQT×Tenure / 10		0.3926*	0.2349	1.3379**
		(9.2133)	(0.2122)	(0.6015)
AFQT×Tenure^2 / 100		-0.3571*		-1.3492**
		(0.1797)		(0.5676)
N	3843	3843	3843	3843

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

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