Employer Learning Under Asymmetric Information: The Role of Job Mobility*

Ye Zhang†

This Version: June 1, 2007

Abstract

This paper develops an asymmetric employer learning model in which endogenous job mobility is both a direct result of intensified adverse selection and a signal used by outside employers to update their expectations about workers' productive ability. The previous literature on asymmetric employer learning builds on two-period mover-stayer models and finds little empirical evidence of the differential impacts of ability and education on wages across tenure levels. This paper extends the mover-stayer framework by allowing the employment history to be observed by recruiting firms in a three-period model. I derive new empirical implications regarding the relationship between wage rates, ability, schooling and overall measures of job mobility. Testing the model with data from the National Longitudinal Survey of Youth 1979 (NLSY-79), I find strong evidence supporting the three-period asymmetric employer learning model.

*I am most grateful to Jeffrey Smith and Judith Hellerstein for their insightful comments, invaluable guidance and continued encouragement. I have also benefited from discussions with Jorge Aguero, Saku Aura, Emek Basker, Pedro Carneiro, William Evans, David Fairris, Jonah Gelbach, Ted Joyce, Mindy Marks, Peter Mueser, June O'Neill, John Rust, Seth Sanders, and workshop participants at the University of Maryland, University of California at Riverside, University of Missouri at Columbia, Baruch College-The City University of New York. All remaining errors are my own.

†Department of Economics, Indiana University-Purdue University Indianapolis, Indianapolis, IN 46202. E-mail address for correspondence: `zhang65@iupui.edu`

1 Introduction

Asymmetric and imperfect information characterize almost every aspect of modern labor market, and economists have been interested in investigating their consequences ever since the seminal work of Akerlof (1970) and Spence (1973). This paper studies an employer's private information about a worker's productivity and argues, theoretically and empirically, that early-career job mobility plays an important role in the employer learning process about employees' productive ability.

In a world where information about workers' productivity is incomplete, it is not possible for a company that is hiring to assess the value of a job candidate's unobserved innate ability. Instead, the potential worker's employment history and other forms of information about his productivity, such as resumes and reference letters, usually serve as the basis for recruitment. This information imperfection directly motivates the statistical theory of discrimination[1] where firms distinguish between individuals with different observable characteristics based on statistical regularities. Although some information about the worker's ability is available to all the firms in the market, it is reasonable to imagine that the incumbent employer accumulates further information about the worker's productive ability after production begins, and then the employer updates its beliefs accordingly. The employer's subsequent wage offers and layoff/firing choices are conditioned on the revised expectations of the worker's productivity. When the current employer and potential employers set their wage rates according to different information sets, the worker's job mobility is endogenously determined by the wage offers from the two sides, and his employment history conveys information regarding his unobserved productivity. The job change pattern of the worker, which is an inevitable consequence of the information asymmetry, provides outside employers with an additional tool to go somewhat beyond the "veil of ignorance" and learn about the worker's productive ability. As intuitively appealing as it sounds, previous research on this topic has neglected the learning process of outside employers through the worker's employment history.

The main contribution of this paper, and the key feature of my employer learning model,

[1] See, among others, Aigner and Cain (1977), Lundberg and Startz (1983), Lang (1986), Coate and Loury (1993), and Oettinger (1996).

is to treat endogenous job mobility[2] as an additional source of information about a worker's productivity that is available to the outside employers.[3] In the context of asymmetric information, job changing as an outcome of market adverse selection can be used by potential employers to assess the quality of the worker. By offering workers with different mobility histories different wage rates, market selection intensifies over time. In contrast, under the hypothesis that learning is symmetric between incumbent and outside employers,[4] job separations have no implications for the worker's expected productivity and mobility plays no role in employer learning. While earlier research on asymmetric information in the labor market recognizes that one consequence of private learning is that workers who switch firms are of lower quality than workers who stay with their employers, it relies on two-period mover-stayer type models and ignores the informational content of job changes. These job changes help outside employers to dynamically acquire extra information about worker productivity.

Using the 1979 cohort of the National Longitudinal Survey of Youth (NLSY-79), and taking advantage of its unique cognitive ability measure, the Armed Forces Qualification Test ($AFQT$) score, which provides a summary of basic math and literacy skills that is not observed by the employers, I test the intensified adverse selection model by examining whether the relationship between a worker's $AFQT$ score and job mobility weakens as workers age. If employer learning is symmetric, the average quality of workers who change jobs will be equal to that of workers who do not. Additionally, if adverse selection does not worsen with the accumulation of labor market experience as implied by the two-period mover-stayer asymmetric employer learning model, then the correlation between the ability measure and the probability of changing jobs should stay constant over time. In contrast, a model in which job mobility serves as an ability signal to outside employers not only implies that the more frequent are job turnovers the lower is the quality of

[2]The model endogenizes job mobility by adding non-pecuniary job characteristics to the worker's utility function. For a similar approach to modeling mobility, see Neal (1998), Acemoglu and Pischke (1998), and Schonberg (2007).

[3]Gibbons and Katz (2001) allow outside firms to learn the reasons for prior job separations and condition their wage offers on them, but in reality, discerning the cause of a prior job change is much more challenging than obtaining the employment history of a job applicant.

[4]The symmetric learning models of Farber and Gibbons (1996) and Altonji and Pierret (2001) do not consider worker mobility at all.

the worker, but it also predicts that unobserved ability plays less and less of a vital role in the mobility decision with each year that the worker spends in the labor market. Thus, this implication empirically differentiates the three models.

I modify the empirical model of Farber and Gibbons (1996) and Altonji and Pierret (2001) by incorporating into the wage regressions they specify the frequency of prior job separations.[5] I show that there is a difference between frequent job movers and occasional movers in terms of how ability affects the way that the incumbent and outside firms set their wage rates conditional on labor market experience. This finding is at odds with the public employer learning model because, in the symmetric learning model, the assumption that the incumbent and recruiting firms have the same amount of information about the worker's ability implies that the $AFQT$ score affects every firm's wage offer in the same fashion given experience. This finding is also not consistent with the two-period mover-stayer model of private learning. If outside employers do not exploit the job mobility history as an additional source of information to distinguish low quality from high quality job candidates, the difference in the impacts of ability on wage rates between the incumbent and outside firms is identical for workers with different mobility levels given the same experience level. However, if the outside firms' wage offers depend on the employment history as described by the three-period model constructed in this chapter, the outside employers will have a more accurate assessment about the productivity of workers with more job changes, so the employer learning more closely resembles public learning for this group of individuals. According to my three-period model, both current employers and outside employers learn, although through different channels. The incumbent employer updates its expectations of the worker's productivity by observing the worker's output and, over time, relies less and less on easily observable characteristics. The outside firms learn over time about productivity through observing the job mobility history of the worker, and these outside employers also depend less and less on variables like years of schooling. The substitution of employment history for schooling as a productivity signal implied by my model

[5] Mincer and Jovanovic (1981) use the frequency of prior moves as a control for individual heterogeneity when estimating the returns to job seniority. I use the coefficients on the interaction terms between prior mobility, test score, job tenure, and years of schooling to test the three-period asymmetric employer learning model.

allows me to test the model by examining the impact of education on wages for individuals with different job turnover patterns.

The paper unfolds as follows. Section 2 provides a review of the employer learning literature. Section 3 presents my employer learning model where a worker's employment history is used by outside firms to revise their expectations about the worker's productivity, and contrasts the empirical implications of my model with those of the public learning and two-period mover-stayer models. Section 4 describes the data and Section 5 presents empirical evidence. Section 6 concludes.

2 Previous Literature on Employer Learning

While it seems plausible that prospective employers may be less informed about the productivity of the worker than the current employer, it is assumptions about how outside firms learn that divide the literature on employer learning. The phrases "symmetric employer learning" or "public learning" refer to the body of research that assumes away asymmetric information and instead assumes that all market participants, incumbent or outside, have the same amount of information about the worker's productivity at each point in time and that the labor market operates competitively. Examples of early theoretical analyses under the hypothesis of public employer learning are Freeman (1977) and Harris and Holmstrom (1982). Another set of studies, including this paper, assume that there is some degree of information asymmetry and that the incumbent employer has more information than other firms about the employee's ability. Under this assumption, recruiting firms have an informational disadvantage relative to current employers. How the outside firms use the information contained in the worker's employment history to minimize this disadvantage motivates this paper. In the literature, efforts have been made to examine how "asymmetric employer learning", or "private learning", might generate inefficient job assignments within the firm; these include the models laid out by Waldman (1984), Milgrom and Oster (1987), and Bernhart (1995). Other theories, such as those of Greenwald (1986) and Lazear (1986), focus on the analogous implications for wage dynamics and job separations.

Two influential papers made empirical breakthroughs in testing the employer learning model: Farber and Gibbons (1996) and Altonji and Pierret (2001). Working under the hypothesis of pure symmetric employer learning, they deliver testable empirical implications that are consistent with the observed patterns in the data for experience gradients, education, and test scores in a wage regression that are hard to reconcile with a simple human capital model. Their models predict that, at labor market entry, firms rely on easy-to-observe variables that are correlated with productivity to determine wage rates. Thus, the coefficient on a variable correlated with productivity which is not observable to employers but is observed by economic analysts should increase with labor market experience. The same argument leads to the decreasing time path of the coefficient on the easy-to-observe variable that is correlated with ability if the hard-to-observe measure of ability is included in the wage regression.[6] Both papers use the NLSY-79 to test their theoretical predictions and obtain broadly supportive results. Their methodology also has been applied to datasets outside of the United States. For example, Bauer and Haisken-DeNew (2001) find some support for the symmetric employer learning model in German data for blue-collar workers, but not for white-collar workers; Galindo-Rueda (2002) obtains similar findings using data from the UK for approximately the same time period as that considered by Altonji and Pierret (2001). More recently, Lange (2005) develops an econometric model to estimate the speed of employer learning,[7] also under the pure symmetric learning assumption. He finds that employers are able to reduce their average expectation error about the productivity of a worker by 50% over the first three years and he concludes that this is rather fast. It is noteworthy that if the current employer and outside employers hold different perceptions about a worker's productivity, then his conclusions may change.

Empirical research on labor market asymmetric information is sparse and far from conclusive. Gibbons and Katz (2001) test the asymmetric learning hypothesis by comparing the earnings

[6] Altonji and Pierret (2001) specify their learning model in logarithms while Farber and Gibbons (1996) specify the model in levels and derive that wages should follow a martingale.

[7] In an earlier paper, Altonji and Pierret (1998) recognize that the speed of employer learning plays a crucial role in statistical discrimination. They argue that the observed coefficient patterns in their earnings equation are consistent with a fast speed of employer learning and that this limits the contribution of signaling to the returns to education.

losses of workers who are laid off versus those who are displaced for exogenous reasons, like a plant closing. Under the assumption that information concerning a worker's ability is private to the current employer, outside market participants infer that laid-off workers are of low quality and label them as "lemons", but no such inference is warranted for exogenous job leavers. Since pre-displacement wages do not differ by cause of displacement for the two groups of workers, their asymmetric learning model predicts a greater wage loss for layoffs than for those displaced by plant closing. Their empirical examination using the CPS Displaced Workers Supplements (DWS) clearly supports their model predictions.[8]

Rodriguez-Planas (2004) extends the adverse selection model of Gibbons and Katz (2001) by allowing recalls of laid-off workers to their original employers and offers a new test of the importance of asymmetric information in the labor market. She argues that if employers have discretion over whom to recall, high-ability workers are more likely to be recalled and may choose to remain unemployed rather than to accept a low-wage job offered early in their unemployment spell. If so, unemployment can serve as a signal of productivity. In this case, her model suggests that unemployment duration may be positively related to post-displacement wages even among workers who are not recalled. In contrast, because workers displaced through plant closings cannot be recalled, a longer duration of unemployment should not have a positive signaling benefit for such workers. Her empirical results using the 1988-2000 DWS reveal that the earnings and unemployment duration experiences of the two groups behave in the predicted way and are consistent with asymmetric information in the labor market.

In a paper closely related to my study, Schonberg (2007) extends the framework of Farber and Gibbons (1996) and Altonji and Pierret (2001) to accommodate the situation in which employer learning is private by endogenizing the mobility decision of the worker. She builds a two-period mover-stayer model and tests it by adding tenure variable to the wage regression and examining whether the effects of education and ability on wage offers differ for incumbent employers and

[8] Hu and Taber (2005) recently challenged the results of Gibbons and Katz (2001) by showing the difference in wage loss between exogenous job leavers and layoffs varies dramatically by race and gender. They offer heterogeneous human capital and taste-based discrimination as possible explanations for the observed patterns for African Americans and females.

outside firms. She finds only limited empirical evidence to support her asymmetric information model for the workers with higher education, after she includes interactions between schooling and the test score variables with higher-order terms in job tenure.[9]

3 The Asymmetric Employer Learning Model

3.1 A Basic Two-Period Model

First, let us consider a simple two-period employer learning model set up in the spirit of Greenwald (1986) and Schonberg (2007) to highlight the way in which asymmetric information and adverse selection distort market transactions. I extend the model to a three-period setting in Subsection 3.2. This model assumes the productivity of individual i in firm j, $\chi_{i,j}$, is given by $\chi_{i,j} = \eta_i + \delta_{i,j}$, where η_i denotes the ith worker's time-invariant innate ability and $\delta_{i,j}$ is the quality of the worker-firm match. The population distributions of η_i and $\delta_{i,j}$ are independent and are common knowledge to all market participants. I further assume that $\eta_i \sim N(\mu_\eta, \sigma_\eta^2)$, $\forall i$ and $\delta_{i,j} \sim N(\mu_\delta, \sigma_\delta^2)$, $\forall i, j$. Jobs are treated as pure search goods in this model[10] and match productivity is known ex ante. In another words, there is no further information on match quality generated in the model as the match proceeds. Following the job matching literature, a new value of $\delta_{i,j}$ is drawn from its distribution with each job change and the successive drawings are independent. This guarantees that the worker's prior employment history is not relevant in assessing his $\delta_{i,j}$ in a newly formed match.[11]

The risk-neutral workers are also heterogeneous with regard to a non-pecuniary utility component, $\theta_{i,t}^j$, associated with job j for time period t.[12] The inclusion of this taste parameter is in

[9]She does not find evidence of asymmetric learning for high school dropouts and high school graduates in her sample.

[10]For "pure-search-good" models of job changes, see, among others, Lucas and Prescott (1974), Burdett (1978), Mortensen (1978), Jovanovic (1979b), and Wilde (1979).

[11]Another line of job search and matching models treats match-specific productivity as an experience good; see, e.g., Johnson (1978), Jovanovic (1979a), and Moscarini (2003), where match quality is not known ex ante but is learned over time as the job is "experienced". In order to concentrate attention on employer learning and sequential adverse selection, and to avoid the complications caused by employee's time varying perceptions of job quality, I model match quality as an inspection good in this paper.

[12]I use employer and job interchangeably in this paper. Empirically, the term "job" refers to any position within

line with most of the existing work on asymmetric employer learning and is part of an easy way to endogenize mobility. As explained by Greenwald (1986), the "random" quit behavior generated by this type of heterogeneity is critical to the existence of equilibrium turnover. In particular, it facilitates trading even in the presence of adverse selection so that the market does not break down completely as in Akerlof (1970). In this model, the non-pecuniary utility measure is assumed to be transitory and workers draw a new value of $\theta_{i,t}^{j}$ in each period for each job. This taste shock may refer to preferences to specific colleagues and supervisors, the working environment, health and other benefit programs, *etc.* I specify the distribution of $\theta_{i,t}^{j}$ as $N(0, \sigma_{\theta}^{2})$ for any i, j, t.

Wage rates are determined on the spot market and long-term contracts of any sort are assumed away. At the beginning of the first period, wages are offered simultaneously by all of the recruiting employers. Firms do not see $\chi_{i,j}$ although they know $\delta_{i,j}$ upon inspection. In addition, after production takes place, the ith worker's output for period 1 in firm j, $y_{i,j,1}$, becomes known to the incumbent firm. The public learning models of Farber and Gibbons (1996) and Altonji and Pierret (2001) assume that the information held by employers is symmetric and all of the firms in the market observe the same sequence of output $(y_{i,j,1}, y_{i,j,2}, ..., y_{i,j,t})$ through period t. In contrast, in my model, the productivity signal is only observed by the worker's current employer. This noisy measurement, $y_{i,j,1} = \chi_{i,j} + \epsilon_{i,j,1}$, is then used by the current firm to update its expectation of the ith individual's productivity. With an additional assumption of an $i.i.d$ normal distribution for $\epsilon_{i,j,t}$, Bayes's rule yields the expected productivity at the end of period one from the perspective of the incumbent employer:

$$E(\chi_{i,j} \mid y_{i,j,1}) = \frac{\sigma_{\epsilon}^{2}}{\sigma_{\eta}^{2} + \sigma_{\epsilon}^{2}}(\mu_{\eta} + \delta_{i,j}) + \frac{\sigma_{\eta}^{2}}{\sigma_{\eta}^{2} + \sigma_{\epsilon}^{2}} y_{i,j,1}. \tag{1}$$

The posterior mean is simply a weighted average of the prior expectation of the worker's productivity and the noise-ridden signal, where the weights depend on the relative sizes of the prior variance and the variance of the noise term $\epsilon_{i,j,1}$. The posterior variance $Var(\chi_{i,j} \mid y_{i,j,1})$ is known

a given employer rather than to a particular position with that employer. The work history file in NLSY-79 does not provide enough information to distinguish job position changes from employer changes.

to be $\frac{\sigma_\eta^2 \sigma_\epsilon^2}{\sigma_\eta^2+\sigma_\epsilon^2}$, which is independent of the realization of $y_{i,j,1}$.

At the beginning of period two, potential employers first make wage offers. The current employer then observes those wage offers and makes a counter offer. This timing of events in wage determination is standard in the literature dealing with asymmetric information.[13] While the key empirical implications of the model remain valid if the second-period wage offers are made simultaneously by the incumbent and outside firms, they are no longer attainable if the current employer makes the first move. In this case, the incumbent firm loses its informational advantage and reveals the productivity of its workers to the entire market by tying wage offers to the productivity signals that only it observes. To avoid a host of game-theoretic strategic considerations that lie beyond the scope of this paper, I maintain the conventional assumption on the timing of wage offers. Observing the wage offers and the new draws of the non-monetary utility component measures $\theta_{i,2}^j$, individual i makes his mobility decision. Assuming risk-neutrality, the utility of job j consists of the sum of the wage offer from employer j and the non-pecuniary taste measure, $w_{i,2}^j + \theta_{i,2}^j$, where $j = c, o$ with c denoting the current employer and o the potential alternative employer. Thus, worker i moves away from his current firm if and only if $w_{i,2}^c + \theta_{i,2}^c \leq w_{i,2}^o + \theta_{i,2}^o$. Making use of the distributional assumption about the unobserved non-pecuniary heterogeneity, the probability of moving is $\Phi(\frac{w_{i,2}^o - w_{2,i}^c}{\sqrt{2}\sigma_\theta})$. All workers are employed in both periods and retire at the end of the second period.

Working backwards from the second period and suppressing the individual subscript i, with the updated expectation of the worker's productivity as well as the outside wage offer w_2^o in hand, the optimization problem for the incumbent firm is

$$\max_{w_2^c} \; (\frac{\sigma_\epsilon^2}{\sigma_\eta^2+\sigma_\epsilon^2}(\mu_\eta+\delta_c) + \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2} y_{c,1} - w_2^c)(1-\Phi(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta})), \tag{2}$$

while the outside employer maximizes

$$\max_{w_2^o} \; (\mu_\eta + \delta_o - w_2^o)\Phi(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta}). \tag{3}$$

[13] See, among others, Waldman (1984), Greenwald (1986), and Gibbons and Katz (1991).

Manipulation of the first-order conditions yields

$$w_2^c = \frac{\sigma_\epsilon^2}{\sigma_\eta^2+\sigma_\epsilon^2}(\mu_\eta+\delta_c) + \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2}y_{c,1} - \sqrt{2}\sigma_\theta \frac{1-\Phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})}, \tag{4}$$

and

$$w_2^o = \mu_\eta + \delta_o - \sqrt{2}\sigma_\theta \frac{\Phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})}. \tag{5}$$

The monotone hazard rate feature of normal random variables, $d(\frac{1-\Phi(\theta)}{\phi(\theta)})/d\theta < 0$, implies the quasi-concavity of the objective functions so that the first-order conditions are sufficient for the maximization problems. The monotone hazard rate also guarantees that the two reaction functions defined by the two first-order conditions both have a positive slope less than one and that there is at most one intersection. The equilibrium exists and is unique.[14]

The wage offer of the current employer depends on the productivity signal sent by the worker. His first-order condition implies

$$\frac{\partial w_2^c}{\partial \eta} = \frac{\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2}}{1 - d(\frac{1-\Phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})})/d(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})} > 0, \tag{6}$$

and

$$\frac{\partial w_2^c}{\partial \delta_c} = \frac{1}{1 - d(\frac{1-\Phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})})/d(\frac{w_2^o-w_2^c}{\sqrt{2}\sigma_\theta})} > 0. \tag{7}$$

In the context of match quality as an inspection good, the higher is the innate ability, the higher is the wage offered by the incumbent firm. The relationship between the current employer's wage offer and the worker's ability is not as strong as the relationship between the incumbent's wage offer and match quality. This simply follows from the different learning mechanisms attached to

[14]This equilibrium is different from the Nash equilibrium of Greenwald (1986) due to our differing assumptions regarding the "random" quit behavior. His analysis relies on the assumption that the probability of quitting equals one if the outside offer is greater than the wage offered by the incumbent firm and equals a fixed value μ if the current employer offers a higher wage rate. As a result of that, firms in his model simply retain high ability workers by matching their outside offers.

the individual's innate ability and to the match-specific productivity. Job match quality is learned instantly, without error ex ante, while ability has to be inferred from a series of noisy signals. As pointed out by Lange (2005), the parameter $\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2}$ plays a central role in the updating process of expected productivity. It represents the noisiness of the initial assessment of productivity relative to the noisiness of the subsequent signals. It is clear from (6) that if subsequent signals are more noisy than the initial expectation, that is, the smaller is $\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2}$, the lower the weight the incumbent firm places on innate ability in wage setting.

At the same time, private information prevents potential employers from obtaining updated expectations of unobserved productivity, as a result, the outside wage offer does not vary with η. Nevertheless, the relationship between the outside wage offer and match-specific productivity is positive, i.e.

$$\frac{\partial w_2^o}{\partial \delta_o} = \frac{1}{1 + d\left(\frac{\Phi(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta})}\right) / d\left(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta}\right)} > 0, \tag{8}$$

which is intuitive given the assumption about the nature of job match quality. The relationship between mobility and ability generated by this model embodies adverse selection, so that

$$\frac{\partial \Phi(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta})}{\partial \eta} = -\frac{1}{\sqrt{2}\sigma_\theta}\phi\left(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta}\right)\frac{\partial w_2^c}{\partial \eta} < 0. \tag{9}$$

That is, the probability of moving to another employer at the beginning of the second period is higher for less able workers. Again, taking the derivative with respect to the current firm's match quality,

$$\frac{\partial \Phi(\frac{w_{2,i}^o - w_{2,i}^c}{\sqrt{2}\sigma_\theta})}{\partial \delta_c} = -\frac{1}{\sqrt{2}\sigma_\theta}\phi\left(\frac{w_2^o - w_2^c}{\sqrt{2}\sigma_\theta}\right)\frac{\partial w_2^c}{\partial \delta_c} < 0. \tag{10}$$

Equation (10), along with (8), captures the notion of a "good match" in the sense that it pays better and survives longer. Match quality has little impact on the implications of asymmetric employer learning highlighted by (7) and (9). Topel and Ward (1992),[15] using longitudinal employee-employer data, indicate that wage gains at job changes average about 10% and account

[15]See Bureau of Labor Statistics (2006) for similar results from the NLSY-79.

for about one third of total wage growth during the first ten years in the labor market. This evidence should not be seen as contrary to the predictions of the asymmetric information model, as the match-specific productivity $\delta_{i,j}$ in my model does allow between-job wage growth, while their study does not deal with the quality of the workers across mobility levels.

To complete the model, I assume that the wage setting game on the entry-level labor market resembles the standard inspection good job matching models and the public learning models. Before period one, none of the firms in the labor market knows more about the productivity of the worker than the initial expectation, the wage offers therefore do not depend on ability. Without loss of generality, I assume only two potential employers $j = J, K$ are competing for workers on the entry-level market. This particular case can be extended readily to the N-firm case. If the firms and workers share the same discount factor β, the ith individual's expected utility when working for firm J is

$$w_1^J + \theta_1^J + \beta \left[\Phi(\frac{w_2^K - w_2^J}{\sqrt{2}\sigma_\theta})(w_2^K + \theta_2^K) + (1 - \Phi(\frac{w_2^K - w_2^J}{\sqrt{2}\sigma_\theta}))(w_2^J + \theta_2^J) \right], \tag{11}$$

where switching J and K yields the utility from working for firm K.

Taking the difference between the utilities from employer J and employer K produces the probability that firm J attracts the ith worker, $\Phi(\frac{w_1^J - w_1^K}{\sqrt{2}\sigma_\theta})$. Therefore, the profit maximization problem for employer J can be written as

$$\begin{aligned} \max_{w_1^J} \Phi(\frac{w_1^J - w_1^K}{\sqrt{2}\sigma_\theta})[\mu_\eta + \delta_J - w_1^J + \beta E_{\eta,\epsilon}((1 - \Phi(\frac{w_2^K - w_2^J}{\sqrt{2}\sigma_\theta}))(\frac{\sigma_\epsilon^2}{\sigma_\eta^2 + \sigma_\epsilon^2}(\mu_\eta + \delta_J) \\ + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\epsilon^2} y_{J,1} - w_2^J))], \end{aligned} \tag{12}$$

where $E_{\eta,\epsilon}$ denotes the expectation with respect to random variables η and ϵ. Replacing subscript J with K defines the optimization problem facing firm K. The symmetry implies that in the entry-level market equilibrium, both firms offer the same wage conditional on match quality, just as in the case of public learning, and better match quality commands a higher wage rate. Combining match-specific productivity and adverse selection on unobserved innate ability together implies that, although a "mismatch" leads to a lower wage and an early separation, job matching alone does not predict that movers are of lower quality than stayers, which is an important prediction from the two-period model.

3.2 A Three-Period Extension with Empirical Implications

While the two-period mover-stayer model does capture how private information held by the current employer affects the worker's mobility decision and wage determination, it is silent about the role of job mobility in sequential market trading, and it treats potential recruiting firms as completely "passive". The extension to a three-period setting allows the employment history of the workers on the second-hand labor market to serve as another signal to outside firms and provides an additional channel for recruiting employers to learn about the unobserved productivity of the workers. The two-period model suggests that worker ability and job mobility are negatively correlated because of adverse selection. It is reasonable to think that outside employers take prior job mobility into account when they make subsequent wage offers. The three-period extension also sharply contrasts with the match quality story of job mobility, in which the prior employment history is independent of the quality of a new match. Here, prior employment history is the driving force behind dynamic adverse selection.

From the perspective of potential employers, at the end of period two workers can be distinguished by their mobility decisions in the previous period. Conditional on each of the two possible values of the number of job changes, $m = 0, 1$, the bidding procedure is completely comparable to the one at the end of the first period. The only difference is that the recruiting firms now know that the distribution of η is different for workers with different m because market selection takes place at the end of period one. For workers with $m = 1$, that is, those who change jobs at the end of period one, the expected productivity becomes

$$E(\chi_j \mid m = 1) = E(\eta \mid w_2^c \leq w_2^o + \theta_2^o - \theta_2^c) + \delta_j. \tag{13}$$

Given that $\frac{\partial w_2^c}{\partial \eta} > 0$ and that everything else in the conditioning set of the expectation of η is independent of η, the end-of-period-one adverse selection shifts the ability distribution of the $m = 1$ workers toward the left. Similarly, asymmetric employer learning shifts the distribution of η for the stayers toward the right.

Meanwhile, the incumbent firms of workers with $m = 0$ continue learning in the Bayesian style. Their updated expectation is

$$\frac{\sigma_\epsilon^2}{2\sigma_\eta^2 + \sigma_\epsilon^2}(\mu_\eta + \delta_c) + \frac{2\sigma_\eta^2}{2\sigma_\eta^2 + \sigma_\epsilon^2}\frac{(y_{c,1} + y_{c,2})}{2}. \tag{14}$$

For the current employer of workers with $m = 1$, expected productivity takes the form of (1.1).

With repeated market transactions as in the three-period model, potential employers make offers to workers with $m = 1$ according to

$$\max_{w_3^{o',1}} \; (E(\eta \mid w_2^c \leq w_2^o + \theta_2^o - \theta_2^c) + \delta_{o'} - w_3^{o',1})\Phi(\frac{w_3^{o',1} - w_3^{c',1}}{\sqrt{2}\sigma_\theta}), \tag{15}$$

and make offers to workers with $m = 0$ according to

$$\max_{w_3^{o',0}} \; (E(\eta \mid w_2^c > w_2^o + \theta_2^o - \theta_2^c) + \delta_{o'} - w_3^{o',0})\Phi(\frac{w_3^{o',0} - w_3^{c',0}}{\sqrt{2}\sigma_\theta}), \tag{16}$$

where c' and o' denote the incumbent and outside employers at the end of period two and the numerical superscript on w_3 represents the value of m. We further obtain the corresponding optimization problems for the current firms

$$\max_{w_3^{c',1}} \; (\frac{\sigma_\epsilon^2}{\sigma_\eta^2 + \sigma_\epsilon^2}(\mu_\eta + \delta_{c'}) + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\epsilon^2}y_{c',2} - w_3^{c',1})(1 - \Phi(\frac{w_3^{o',1} - w_3^{c',1}}{\sqrt{2}\sigma_\theta})), \tag{17}$$

and

$$\max_{w_3^{c',0}} \; (\frac{\sigma_\epsilon^2}{2\sigma_\eta^2 + \sigma_\epsilon^2}(\mu_\eta + \delta_{c'}) + \frac{\sigma_\eta^2}{2\sigma_\eta^2 + \sigma_\epsilon^2}(y_{c',1} + y_{c',2}) - w_3^{c',0})(1 - \Phi(\frac{w_3^{o',0} - w_3^{c',0}}{\sqrt{2}\sigma_\theta})). \tag{18}$$

Comparing (15) and (16) with (3), it is easy to see that the outside wage offers for $m = 0$

individuals exceed those for $m = 1$ workers because $E(\eta \mid w_2^c > w_{2,i}^o + \theta_i^o - \theta_i^c) > E(\eta \mid w_{2,i}^c \leq w_{2,i}^o + \theta_i^o - \theta_i^c)$. Movers, those with $m = 1$, are adversely selected and have a worse η distribution than workers with $m = 0$. The labor market recognizes this in the third period by offering them lower wage rates. This is in contrast with the basic two-period framework where the equilibrium wage on the second-hand market does not depend on η, as suggested by (3). Previous research on asymmetric employer learning stops with the two-period framework and compares quality between movers and stayers in terms of some aptitude test scores such as the $AFQT$ score. However, that approach neglects the intensified adverse selection that is induced in a third period and beyond by the information contained in the worker's employment history, and does not generate empirical implications about the time path of the effect of ability on the wage offers from the incumbent and from the outside employers. The three-period extension argues that the correlation between the outside market equilibrium wage and unobserved ability increases with labor market experience and that market selection intensifies dynamically, so that

$$\frac{\partial \Phi(\frac{w_3^{o'} - w_3^{c'}}{\sqrt{2}\sigma_\theta})}{\partial \eta} = \frac{1}{\sqrt{2}\sigma_\theta}\phi(\frac{w_3^{o'} - w_3^{c'}}{\sqrt{2}\sigma_\theta})(\frac{\partial w_3^{o'}}{\partial \eta} - \frac{\partial w_3^{c'}}{\partial \eta}) < 0. \tag{19}$$

Although (19) is negative,[16] meaning that workers with lower values of η are still more likely to change jobs, the additional positive component $\frac{\partial w_3^{o'}}{\partial \eta}$ means fewer job changes after the second period than after the first period.[17] There is an enormous amount of heterogeneity among movers and an important tool for potential recruiting firms that want to learn about this heterogeneity is job mobility history. A typical two-period analysis, such as Schonberg (2007), predicts that the ability gradient of the job separation probability remains constant over time. In contrast, in the three-period case, incumbent firms gradually lose their informational advantage due to the accumulation of knowledge about η by outside employers with the result that employer learning on the market place converges to the public learning model over time. The intensified adverse selection

[16]This is because the current employer still holds more information about η than the outside market, so that, $\frac{\partial w_3^{o'}}{\partial \eta} - \frac{\partial w_3^{c'}}{\partial \eta} < 0$.

[17]See Greenwald (1986) for a similar argument.

implies a decreasing effect of innate ability on the job change probability. It is also obvious from (19), but still worth mentioning, that if the output sequence $(y_{j,1}, y_{j,2}, ..., y_{j,t})$ is available to all the firms, then $\frac{\partial w_t^o}{\partial \eta} = \frac{\partial w_t^c}{\partial \eta}$ and $\frac{\partial \Phi(\frac{w_t^o - w_t^c}{\sqrt{2}\sigma_\theta})}{\partial \eta} = 0$ for any t. When the information is imperfect but symmetric, the ability distribution is identical across mobility levels and the worker's job changing decision depends on the match quality δ and the non-pecuniary job characteristics θ.[18]

The first-order condition for (18) combined with (6) allows us to obtain

$$\frac{\partial w_3^{c',0}}{\partial \eta} = \frac{\frac{2\sigma_\eta^2}{2\sigma_\eta^2+\sigma_\epsilon^2} + [d(\frac{1-\Phi(\frac{w_3^{o',1}-w_3^{c',1}}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_3^{o',1}-w_3^{c',1}}{\sqrt{2}\sigma_\theta})})/d(\frac{w_3^{o',1}-w_3^{c',1}}{\sqrt{2}\sigma_\theta})]\frac{\partial w_3^{o',0}}{\partial \eta}}{1 - d(\frac{1-\Phi(\frac{w_3^{o',0}-w_3^{c',0}}{\sqrt{2}\sigma_\theta})}{\phi(\frac{w_3^{o',0}-w_3^{c',0}}{\sqrt{2}\sigma_\theta})})/d(\frac{w_3^{o',0}-w_3^{c',0}}{\sqrt{2}\sigma_\theta})} > \frac{\partial w_2^c}{\partial \eta}. \tag{20}$$

This inequality explicitly spells out employer learning: for workers staying with their initial employers for the entire three periods, wage rates depend more and more on unobserved productivity. Moreover, and perhaps more importantly, this increase in the correlation between wages and ability is larger than that in the pure symmetric employer learning model. To see this, notice that the numerator of $\frac{\partial w_3^{c',0}}{\partial \eta}$ has two parts. The first term comes from the current employer learning more over time, as argued by Farber and Gibbons (1996) and Altonji and Pierret (2001), i.e. $\frac{2\sigma_\eta^2}{2\sigma_\eta^2+\sigma_\epsilon^2} > \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2}$, where $\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\epsilon^2}$ appears as the numerator of (6). The second term is a special feature of this model and follows directly from the market feedback of the job mobility decision. It represents the additional premium put on unobserved productive ability by the current employer because he knows that outside recruiting firms can partially learn about the ability of the workers via the employment history. Existing asymmetric employer learning models have been unable to lay this out clearly and convincingly because they do not take into account the signaling effect of job mobility on outside wage offers.

For workers who change jobs after period one, the increase in the correlation between market wage rates and innate ability η over time also holds. The wage determination process in (3)

[18] Jovanovic (1979a) (footnote 11, p. 982) writes "...in other words, the model does not imply that "movers" should do worse than "stayers" even though empirically this appears to be true..."

implies that for $m = 1$ workers, wage offers for period two are constant over η because only μ_η enters (3), but the story told by (15) and (17) is that whether or not these workers decide to change jobs at the end of the second period, it is always the case that $\frac{\partial w_3^{o',1}}{\partial \eta} > 0$ and $\frac{\partial w_3^{c',1}}{\partial \eta} > 0$. The three-period asymmetric employer learning model agrees with the public learning models and the earlier two-period analyses of private employer learning in that wages are increasingly correlated with unobserved productivity as labor market experience accumulates. It departs from existing studies in terms of its implications for the differential returns to ability for people with different job changing patterns, even conditional on labor market experience and job tenure.

Public information makes $\frac{\partial w_2^c}{\partial \eta} = \frac{\partial w_2^o}{\partial \eta}$ and $\frac{\partial w_3^{c',1}}{\partial \eta} = \frac{\partial w_3^{c',0}}{\partial \eta} = \frac{\partial w_3^{o',1}}{\partial \eta} = \frac{\partial w_3^{o',0}}{\partial \eta}$, at any point in time, for workers with the same amount of labor market experience. All the wage offers, no matter where they come from, depend on η in the same way, given the independence of η and match quality δ. And, individuals with different patterns of prior job separations have the same returns to unobserved productive ability. The two-period mover-stayer model in Schonberg (2007) recognizes that innate ability has a stronger impact on wage offers for incumbent firms than for outside employers, and that the difference is greater as the informational advantage of the incumbent firm increases. Based on this implication, Schonberg (2007) predicts a positive coefficient on the variable that interacts the $AFQT$ score and job tenure in a wage regression. While in general this intuition still holds for the three-period model, the absence of learning from outside employers in the two-period model implies the independence of job mobility frequency and the differential impacts of ability on wages offers from current and potential employers. In the three-period model, when recruiting firms on the outside market take job mobility history into consideration at the end of period two, the informational advantage of the current firm in period two is lower than that in period one and the reduction is higher for workers with more frequent job changes. The more information the outside firms have, the smaller is the difference between the impacts of ability on wages for the incumbent versus outside firms. This implication is not consistent with the mover-stayer model in which learning by recruiting employers is ruled out. Thus, the signaling effect of the prior job moves implies a negative coefficient for the variable which interacts the test score, job tenure, and frequency of job mobility.

One real world application of employer learning models is to study statistical discrimination, where firms distinguish among workers on the basis of easily observable variables that may be correlated with productivity like years of eduction, gender, and race. Altonji and Pierret (2001) describe the intuition of such analyses succinctly:

"As employers learn about the productivity of workers, s [which is schooling] will get less of the credit for an association with productivity that arises because s is correlated with z [a variable like AFQT score that is initially unobserved, but is positively correlated with both s and output], provided that z is included in the wage equation with a time dependent coefficient and can claim the credit."

Note that because a worker's education level is part of the firm's initial information set and is incorporated into the determination of first-period wages, subsequent innovations in wages can not be forecast from years of schooling.[19] The empirical regularity of a declining time path of the returns to schooling arises solely out of the relationship between education and unobserved innate ability. To include easily observed time-invariant characteristics like schooling in the model, I can redefine productivity as

$$\chi_j = rs + \eta + \delta_j, \tag{21}$$

where s denotes the years of schooling. Keeping everything else in the model unchanged, the time path of the returns to η is shown to be increasing as firms accumulate more information, regardless of whether it is symmetrically or asymmetrically distributed between the incumbent and potential employers. This learning effect on the impact of ability spills over to the schooling variable that firms use to statistically discriminate among new employees. Thus, following the same logic as in Altonji and Pierret (2001), given $cov(\eta, s) > 0$, the model predicts that the coefficient on s in a wage regression declines with labor market experience when an ability measure unobservable to employers is included.

[19] Farber and Gibbons (1996) make this point and predict a zero coefficient on the interaction term between education and experience when the residualized $AFQT$ score is included in a wage regression.

Unlike years of schooling, which is a time-invariant ability signal known to all the employers upon market entry, the job mobility history serves as a time-varying signal to the outside firms in the three-period model. The information contained in a worker's employment history is utilized by potential hiring firms to evaluate the productivity of the workers. The fact that learning by the outside firms increasingly makes the time-invariant signal s redundant is another special feature of the three-period model. Traditional analyses ignore the informational content of prior job moves and imply that the effect of education on wages is independent of job mobility, conditional on experience and job tenure. The signaling effect of employment history, however, predicts a negative coefficient associated with the interaction between years of schooling and the frequency of job mobility in a wage regression.

4 The Data: NLSY-79

The empirical work is based on White, Black, and Hispanic males from the 1979-2000 waves of the National Longitudinal Survey of Youth (NLSY-79). A key feature of the NLSY-79 is that in addition to detailed information on family background, scholastic achievement, and labor market outcomes, its work history file provides an unusually complete picture of employment for a cohort of young workers during a period when they have made transitions from school to work. This includes records of virtually every job held. As a result, it is ideal for my study. The original NLSY-79 sample consists of 12,686 men and women (age 14-22 in 1979) who were interviewed annually between 1979 and 1994 and biennially from 1996 to the present. There are three subsamples in the NLSY-79: a cross-sectional sample representative of young people; a supplemental sample designed to oversample Hispanic, Black, and economically disadvantaged White youth; and a sample designed to represent the population of those enlisted in one of the four branches of the military. I exclude the military subsample from my analysis because, following the 1984 interview, the military subsample were no longer eligible for interview and it is hard to construct a long enough employment series for respondents from this subsample.

In order to abstract the analysis from family and fertility decisions and focus on a subpopulation with strong labor force attachment, I use male sample only. There are 5579 males in the original NLSY-79 sample after eliminating the military respondents. I exclude employment and wage observations from before a person leaves school and begins to accumulate labor market experience, and only count job changes from that point. My definition of the school-to-work transition date follows that of Altonji and Pierret (2001):[20] the month and year of the respondent's most recent enrollment in school at the first interview when the respondent is not currently enrolled. I lose 49 individuals from the original sample because their school exit date is indeterminate according to this definition. I also exclude 1137 individuals whose labor market entry occurs before January 1978. Detailed information on employment activities is only reported from that date onwards in the work history file, so I can not construct accurate measures of overall mobility, work experience, and job tenure for workers who start their careers before January 1978. Additionally, I delete 47 individuals because their actual labor market experience or job seniority is indeterminate and another 12 individuals whose wage information is unreasonable, which brings the sample size down to 4334. Furthermore, 202 individuals in the sample did not take the Armed Services Vocational Aptitude Battery[21] (ASVAB) tests which are used by the NLSY-79 to construct the $AFQT$ score.[22] After dropping them, the remaining sample consists of 4132 individuals with 48,617 person-year observations.

Table 1 contains summary statistics for observations used in the analysis. Actual labor market experience is the number of weeks in which the worker works more than 30 hours divided by 52 after the transition from school to work. I do not count part-time employment, self-employment, time spent working without pay, time spent unemployed, and time spent out of the labor force.[23]

[20]Alternatively, Farber and Gibbons (1996) define a transition as occurring if the worker is classified as non-working for at least one year, followed by at least two consecutive years classified as working, where a worker is classified as working when she has worked at least 26 weeks, and during these weeks at least 30 hours, since the last interview.

[21]The $AFQT$ score is the sum of the raw scores from the following four sections of the ASVAB: arithmetic reasoning, word knowledge, paragraph comprehension, and one half of the score from numerical operations section.

[22]The ASVAB was administered to the NSLY-79 respondents in 1980, thus, different respondents took it at different ages. To eliminate age effects, I standardize the $AFQT$ score within each birth cohort.

[23]For the individuals who work more than one job at a point in time, I only consider the job at which the respondent works the most hours during the week.

Job tenure is calculated as the number of weeks divided by 52 spent in full-time employment with the same employer. The wage measure is the hourly wage at the beginning of each employment spell from the NLSY-79 work history file. Wages are deflated by the Consumer Price Index with 2002 as the base year; values below $1 and above $300 are considered unreasonable and dropped.[24]

The job mobility count is obtained from the work history file of the NLSY-79, which reports the starting dates for the jobs held at the time of each interview, as well as for up to five jobs[25] that began and ended since the last interview. I link all the jobs across survey years[26] and construct a complete employment history for each individual in the sample. The frequency of job mobility is calculated as the individual's mean number of prior job separations as of time t. Table 2 shows the distribution of the number of job separations by each worker during the first 2, 5, and 10 years of his career as well as the total number of jobs held.

The average number of job separations in the first ten years is 5.6 with a standard deviation of 4.0. The mean number of jobs actually held[27] is 6.2 with a standard deviation of 4.0. Table 2 also illustrates that only 3% of individuals experience no job changes in the first 10 years of their career, while around 10% of workers remain with their initial employers during the first five years and 38% for the first two years. At the other extreme, 11% of individuals separate from 10 or more employers within the first ten years after the school to work transition; that is, they average over one job separation per year for the 10-year period. Table 2 demonstrates that the typical individual in the sample is quite mobile early in his career.

The data on job separations also suggest that job mobility slows over time. While this can not be said to be attributable solely to the intensified adverse selection, it is at least consistent with the three-period model where outside employers take the employment history into account. In

[24] I tried other cutoff values, such as $0.5 and $200. My empirical results are not sensitive to the changes in the values used to define unreasonable wage observations. See Bollinger and Chandra (2005) for more on this issue.

[25] The NLSY-79 collects information on all jobs held by a respondent since the last interview, however, the percentage of respondents who report more than five jobs in each survey year is less than 1%.

[26] As the same employer can receive different job codes across survey years, it is necessary to use beginning and ending dates as well as a series of matching variables to determine the job code in the previous survey for every employer in the current survey and to decide whether it is a new job.

[27] Topel and Ward (1992) find that the average worker holds 6.1 jobs by the time he or she has eight years of potential labor market experience in their longitudinal employer-employee data.

contrast, neither the symmetric employer learning model nor the two-period mover-stayer model implies a decline in job turnover conditional on innate ability. About 30% of the sample undergoes no job changes during the second five years, and 46% undergoes at most one job separation during that time period.

Throughout the paper, I use the total number of job separations rather than the number of voluntary job separations. It is not clear how to distinguish between involuntary and voluntary job separations in the NLSY-79. The NLSY-79 codes a large number of reported reasons for each job separation, including "bad working condition", "own illness", "found better job", "spouse changed jobs", *etc.* If I delete all job separations corresponding to "layoff" and "discharged/fired", then 70% of all the job separations remain. However, those remaining job separations still include ones caused by family reasons as well as ones caused by "found better job" and "pay too low". Moreover, the explanation for over 25% of all job exits is coded as either "other" or missing, so I must either eliminate those jobs or arbitrarily assign them to voluntary or involuntary categories.

5 Econometric Specification and Empirical Results

One of the empirical implications of an employer learning model in which information about a worker's productivity is public is a correlation of zero between the worker's innate ability and his probability of changing jobs. Both the two-period mover-stayer model of asymmetric employer learning and my three-period extension challenge this by showing that the average quality of the job-changing pool is lower than that of the pool of stayers. What differentiates these two versions of the asymmetric information model is the prediction regarding how the relationship between ability and the job change probability changes over time. In the absence of learning by outside employers, the mover-stayer story implies a constant correlation between η and the probability of job change. On the other hand, information accumulation by potential employers through the observed job mobility history implies that this relationship becomes weaker and weaker over time.

I test this implication of the learning model by estimating a probit model where the dependent variable is an indicator of whether the worker experiences a job changes in a given period,

$$\begin{aligned} Pr(JobChange_{i,t} = 1) =& \Phi(\beta_0 + \beta_1 AFQT_i + \beta_2 (Exp_{i,t}/10) \\ &+ \beta_3 (AFQT_i \times Exp_{i,t}/10) + \beta_X' X_{i,t}), \end{aligned} \tag{22}$$

where i is an individual, t is a survey year, $Exp_{i,t}$ is actual labor market experience and $X_{i,t}$ is a vector of other control variables. Throughout the empirical analysis, I normalize all the interactions between schooling and the $AFQT$ score with experience to represent the change in the regression slope between $Exp = 0$ and $Exp = 10$. Also, all of the standard errors reported in this paper are based on White/Huber standard errors that account for arbitrary forms of heteroskedasticity and correlation among the multiple observations for each individual. All of the estimates in this paper are weighted by the sampling weights provided by the NLSY-79. Coefficients β_1 and β_3 should both be zero under the assumption of public learning. All of the asymmetric learning models imply a negative β_1, but only a model with a signaling effect of the job mobility history implies a positive coefficient β_3.

The results of the job changing regressions are presented in Table 3. Column (1) in the table is the mean derivative estimated from a probit model where the standardized $AFQT$ score is the only explanatory variable. A one standard deviation increase in the test score is accompanied by a 3.6 percentage point decrease in the probability of changing jobs. This preliminary evidence clearly rejects the symmetric employer learning hypothesis via a highly statistically significant probit marginal effect associated with the $AFQT$ score. To distinguish the two types of asymmetric learning hypotheses, column (2) estimates the same probit with experience and the interaction between the $AFQT$ score and experience as additional independent variables. The mean marginal effect on the $AFQT$ score remains statistically significant, and there is a positive and statistically significant estimate for the interaction term of the $AFQT$ score and labor market experience. The decreasing time path of the absolute value of the impact of the $AFQT$ score on the probability of changing jobs is a unique prediction from the three-period adverse selection model. It captures the closing of the informational gap between current and outside employers about the productivity of the workers. The estimated marginal effect of 0.026 strongly suggests that not only does the current employer learn, but potential employers also accumulate new information about a worker's innate ability, so that over time ability matters less and less in job changes.

Including additional covariates in the probit regression, column (3) controls for race, industry and occupation, and year effects. These control variables weaken the correlation between the *AFQT* score and job mobility, but by no means eliminate it. The probit marginal effects associated with the *AFQT* score and the interaction term are still statistically significant and qualitatively tell the same story as column (2). Hansen, Heckman, and Mullen (2004) find strong evidence in the NLSY-79 suggesting that schooling is an important determinate of measured achievement such as the ASVAB scores;[28] their estimated increase in the *AFQT* score per year of education for the average person is 0.17 standard deviation. To deal with the effect of schooling on the test score, I construct the educational level and school enrollment status at the ASVAB test date for each individual in the sample[29] and include them in the probit regression of column (4). Putting schooling information as of the test date into the model substantially reduces the magnitude of the probit coefficients: the estimated marginal effects of the *AFQT* score and the interaction term stand at -0.012 and 0.014, respectively. Nevertheless, both are statistically significant at the 5% level, and the overall conclusion is the same as that drawn from column (2) and column (3). To summarize, the probit estimates shown in Table 3 are consistent with an asymmetric employer learning model in which both the incumbent and the outside employers gather information about the worker's unobserved productivity. The negative and statistically significant mean marginal effect of the *AFQT* score on the job change probability rejects the public learning hypothesis, and the gradually decreasing association between the test score and the probability of job separation

[28]See Neal and Johnson (1996) and Cascio and Lewis (2006) for a similar result.

[29]The ASVAB was administered during July–October 1980. Respondents in the NLSY-79 were interviewed during January–August 1980 and January–July 1981. The NLSY-79 also includes a measure of schooling and enrollment status as of May 1 of each survey year. Since the academic year commonly ends in June, individuals advance to a higher completed grade level in June. I use the highest grade completed and enrollment status as reported in the 1980 survey as schooling and enrollment values at the test date if the interview was conducted during July–August 1980, and I use the variables reported in 1981 if the interview was conducted during January-April 1981. For the remaining respondents, I use the variables for May 1, 1981.

is at odds with the two-period mover-stayer model.

To further distinguish the two versions of asymmetric employer learning models, one without outside employers learning and the other with potential firms learning through the employment history of the job candidate, I make use of the empirical framework advanced by Farber and Gibbons (1996) and Altonji and Pierret (2001). Under the assumption of pure public learning, Altonji and Pierret (2001) estimate a version of the standard earnings equation with schooling and the $AFQT$ score interacted with labor market experience

$$\begin{aligned}\ln w_{i,t} =& \alpha_0 + \alpha_1 Schooling_i + \alpha_2 AFQT_i + f(Exp_{i,t}/10) + \\ & \alpha_3(Schooling_i \times Exp_{i,t}/10) + \alpha_4(AFQT_i \times Exp_{i,t}/10) + \alpha_X' X_{i,t} + \xi_{i,t},\end{aligned} \tag{23}$$

where the log wage for the ith worker at time t depends on his schooling, his $AFQT$ score, labor market experience, and other observable characteristics $X_{i,t}$. Their model shows that when the $AFQT$ score is included in the regression as an ability measure, the time path of the coefficient on schooling declines with experience while the coefficient on the $AFQT$ score increases with labor market experience. As employers learn more about the productive ability of a worker, they rely less on the easily observable variables such as education in the wage setting process. Note that my model in Section 3 explicitly demonstrates that their implications regarding the signs of α_3 and α_4 also hold even when the information about the worker's productivity is asymmetric.

Table 4 shows the results generated when their wage regressions are run on my sample. In addition to the explanatory variables shown in the table, all of the regressions control for race, a cubic in experience, industry and occupation, year effects, education interacted with year effects, and Black and Hispanic interacted with year effects. The first two columns report OLS estimates of (23). Columns three and four report two stage least squares (2SLS) estimates using potential experience as an instrument for actual labor market experience.[30] Looking across the columns, the two sets of coefficient estimates tell the same story and confirm the empirical findings of Altonji

[30] Altonji and Pierret (2001) argue that the implications of employer learning for the wage equation may change if the intensity of work experience conveys information to employers about worker quality.

and Pierret (2001) that the impact of the $AFQT$ score on wages increases with labor market experience and the coefficient on years of schooling decreases with experience.

While these estimates support the view that employers acquire new information about workers' productivity over time, they do not allow us to distinguish among public learning, asymmetric learning without the outside employer accumulating new information, and the three-period model developed in the Section 3. When the recruiting employers gather new information about the ability of the worker through his employment history, my model predicts a declining difference between the impacts of ability on wage offers from the incumbent and the outside firms with increasing job mobility, and therefore a negative coefficient for the interaction term involving the $AFQT$ score, job tenure, and the frequency of job mobility. I estimate the following wage regression,

$$\begin{aligned}\ln w_{i,t} =& \gamma_0 + \gamma_1 Schooling_i + \gamma_2 AFQT_i + f_1(Exp_{i,t}/10) + f_2(Tenure_{i,t}/10) + \\ & \gamma_3 Freq_{i,t} + \gamma_4(Schooling_i \times Exp_{i,t}/10) + \gamma_5(AFQT_i \times Exp_{i,t}/10) + \\ & \gamma_6(AFQT_i \times Tenure_{i,t}/10) + \gamma_7(AFQT_i \times Freq_{i,t}) + \\ & \gamma_8(AFQT_i \times Tenure_{i,t}/10 \times Freq_{i,t}) + \gamma_X' X_{i,t} + u_{i,t}, \end{aligned} \tag{24}$$

where $Tenure_{i,t}$ denotes job tenure and $Freq_{i,t}$ denotes the ith worker's frequency of job mobility as of time t. The closing informational gap between the current and outside firms through employment history implies that $\gamma_8 < 0$. On the other hand, if the outside employers ignore the information concerning the worker's innate ability contained in the job mobility history as described in the two-period model, or if their learning process occurs through other channels, then we would expect to find $\gamma_8 = 0$.

The OLS estimates of (24) are displayed in Table 5. Other covariates that I control for are a cubic in experience, a cubic in job tenure, race, industry and occupation, year effects, education interacted with experience, education interacted with year effects, and interactions between the race dummies and the year effects. Column (1) provides the regression estimates before controlling the measure of job mobility. This coincides with existing tests of the asymmetric employer learning model such as those in Schonberg (2007). If employer learning is private, the impact of ability on the wage offer of the current employer exceeds that of the outside firms, which predicts $\gamma_6 > 0$ in (24), as opposed to the case of pure symmetric learning which implies $\gamma_6 = 0$. In line with Schonberg (2007), my estimate for the coefficient associated with the interaction term between the $AFQT$ score and job tenure shows a positive sign that is consistent with the asymmetric information model but fails to pass the significance test at conventional levels. Schonberg (2007) only finds a marginally significant estimate for γ_6 after controlling for interactions between the $AFQT$ score and higher order tenure terms for her university graduates sample.

Column (2) of Table 5 estimates a complete version of (24) and paints a different picture. Although the positive coefficient estimate of 0.021 for the $AFQT$ score and job tenure interaction, larger in magnitude compared to column (1), remains statistically insignificant, the estimated coefficient of -0.013 associated with the interaction between the $AFQT$ score, job tenure, and the frequency of job mobility strongly suggests that outside employers indeed acquire knowledge about the worker's ability through his job change pattern, with the result that the informational discrepancy between the incumbent and potential employers in turn diminishes with experience. Conditional on job tenure, I still see a positive and statistically significant coefficient estimate of 0.049 for the variable interacting experience and the $AFQT$ score, which reinforces the conclusion that learning on the labor market is not purely asymmetric. I also find a negative coefficient estimate for the frequency of job mobility[31] which suggests that early-career mobility does little to help but can do a significant amount to hurt wages. Although this may not be a defining implication from the model, it is consistent with the intensified adverse selection story.

As a time-varying signal of the worker ability, the availability to the market of job mobility history also has implications for the role played by the time-invariant observables that the employers initially use to statistically discriminate among workers. To study how the worker's career path affects the employer learning through easy-to-observe characteristics like schooling, I estimate a

[31] See Light and McGarry (1998) for similar findings.

wage equation of the type

$$
\begin{aligned}
\ln w_{i,t} =& \lambda_0 + \lambda_1 Schooling_i + \lambda_2 AFQT_i + f_1(Exp_{i,t}/10) + f_2(Tenure_{i,t}/10) + \\
& \lambda_3 Freq_{i,t} + \lambda_4 (Schooling_i \times Exp_{i,t}/10) + \lambda_5 (AFQT_i \times Exp_{i,t}/10) + \\
& \lambda_6 (Schooling_i \times Ten_{i,t}/10) + \lambda_7 (AFQT_i \times Tenure_{i,t}/10) + \\
& \lambda_8 (Schooling_i \times Freq_{i,t}) + \lambda_9 (AFQT_i \times Freq_{i,t}) + \lambda_X' X_{i,t} + v_{i,t}. \qquad (25)
\end{aligned}
$$

Table 6 reports the OLS estimates of (25) where X contains the same additional variables as in Table 5. Column (1) excludes the job mobility measure and its interactions with schooling and the $AFQT$ score. Although the general pattern of the coefficients on the interactions between the $AFQT$ score and schooling with experience suggested by the learning model is still borne out by the data, the highly imprecise estimates for λ_6 and λ_7 tell us nothing about the nature of employer learning. In column (2) of Table 6, the estimates support the three-period model in which potential employers learn from the job mobility patterns. In particular, the negative and significant coefficient estimate for the interaction term of schooling and the frequency of job mobility implies that education plays less of a signaling role as outside firms rely more on employment history to assess the value of the worker's productivity. Information revelation as an immediate consequence of intensified adverse selection helps the recruiting firms to become better informed about the quality of the workers in the job-changing pool. Also, the coefficient on the interaction of education and job tenure is negative, though only significant at the 10 percent level. It provides suggestive evidence that potential employers depend more, relative to the incumbent employer, on schooling to determine their wage offers. Taken together, these empirical results strongly surpport the aforementioned three-period model in which not only do incumbent employers learn, but outside firms also actively extract information from workers' employment histories.

6 Conclusion

How do firms learn about their workers' productivity? Do they use easily observed characteristics such as education and race to statistically discriminate among their workers? Do current employers have more information about the worker's productivity than outside firms? If they do, what can outside firms do to minimize their informational disadvantage? During the past decade, labor economists have developed employer learning models to better understand the answers to these questions. Although consensus has been reached, both theoretically and empirically, on the existence of employer learning in the market place, our understanding of whether learning is asymmetric and how the information asymmetry is resolved remains unsatisfactory. This papers builds a learning model under the hypothesis that incumbent employers have superior information about the productivity of its workers. A special feature of my model is that outside employers, by observing workers' job mobility histories, also have access to information about the workers' ability. This attribute differentiates the present model from existing models of asymmetric employer learning that are based on the two-period mover-stayer model. My model also includes a match-specific productivity component that is known ex ante and I show that because the distribution of match quality is independent of worker ability and the quality of previous matches is irrelevant to newly formed job matches, the presence of match-specific productivity does not alter the nature of employer learning about the innate ability of their workers.

It is important to underscore the limits of this study. The literature has long recognized that human capital accumulation may undermine the predictions from learning models. Although the empirical evidence of intensified adverse selection established through our probit estimates is based on a robust feature of the model, the estimates of the wage regressions, especially the coefficient associated with the interaction between the $AFQT$ score and job seniority, also fit a model in which ability aids the acquisition of specific human capital.[32] This complementarity between ability and specific capital implies that more able workers command higher returns to job tenure, which implies a positive coefficient for the interaction term between the $AFQT$ score and job seniority.

[32] See Altonji and Spletzer (1991) for such an example.

It is very difficult to distinguish the present model from a specific human capital model. I can only partially address this concern, following Schonberg (2007), by looking at differential returns to job tenure by education level. The estimate from column (2) of Table 6, even though only marginally significant, implies lower returns for higher educated workers. If we expect individuals with more years of schooling to benefit more from job seniority as the human capital theories imply, my negative coefficient is at odds with such a prediction. My model also rules out the possibility of an experience-good nature of job match, because analysis of an asymmetric employer learning model that also allows learning about the match quality is rather complex and beyond the scope of the current study.

To conclude, the empirical evidence from the NLSY-79 broadly supports the implications from the dynamic adverse selection model: ability is negatively correlated with the probability of changing jobs but this association weakens as young workers advance in their careers; accruing information through observing the employment history on the part of outside firms gradually eliminates the knowledge gap between them and incumbent firms; this in turn reduces over time the difference of the impacts of ability on wage rates between them and the incumbent firm, and allows them to be less dependent on the easy-to-observe characteristics of the workers.

References

[1] Acemoglu, D. and J. Pischke (1998), "Why Do Firms Train? Theory And Evidence." *The Quarterly Journal of Economics*, 113, 78-118.

[2] Aigner, D. and G. Cain (1977), "Statistical Theories of Discrimination in Labor Mrkets." *Industrial and Labor Relations Review*, 32, 175-187.

[3] Akerlof, G. (1970), "The Market for Lemons: Qualitative Uncertainty and the Market Mechanism." *The Quarterly Journal of Economics*, 84, 488-500.

[4] Altonji, J. and C. Pierret (1998), "Employer Learning and the Signaling Value of Education." in I. Ohashi and T. Tachibanaki, eds., *Internal Labour Markets, Incentives and Employment*, London, UK: Macmillan Press.

[5] Altonji, J. and C. Pierret (2001), "Employer Learning and Statistical Discrimination." *The Quarterly Journal of Economics*, 116, 313-500.

[6] Altonji, J. and R. Shakotko (1987), "Do Wages Rise with Job Seniority." *Review of Economic Studies*, 54, 437-459.

[7] Altonji, J. and J. Spletzer (1991), "Worker Characteristics, Job Characteristics, and the Receipt of On-the-Job Training." *Industrial and Labor Relations Review*, 45, 58-79.

[8] Bauer, T. and J. Haisken-DeNew (2001), "Employer Learning and the Returns to Schooling." *Labour Economics*, 8, 161-180.

[9] Bernhart, D. (1995), "Strategic Promotion and Compensation." *Review of Economic Studies*, 62, 315-339.

[10] Bollinger, C. and A. Chandra (2005), "Iatrogenic Specification Error: A Cautionary Tale of Cleaning Data." *Journal of Labor Economics*, 23, 235-257.

[11] Burdett, K. (1995), "Theory of Employee Search: Quit Rates." *American Economic Review*, 68, 212-220.

[12] Bureau of Labor Statistics (2006), "Number of Jobs Held, Labor Market Activity, and Earnings Growth Among the Youngest Baby Boomers: Results from a Longitudinal Survey." *News: United States Department of Labor*, 16-1496.

[13] Cascio, E. and E. Lewis (2006), "Schooling and the Armed Forces Qualifying Test: Evidence from School-Entry Laws." *Journal of Human Resources*, 41, 294-318.

[14] Coate, S. and G. Loury (1993), "Will Affirmative-Action Policies Eliminate Negative Stereotypes?." *American Economic Review*, 83, 1220-1240.

[15] Farber, H. and R. Gibbons (1996), "Learning and Wage Dynamics." *The Quarterly Journal of Economics*, 111, 1007-1047.

[16] Freeman, S. (1977), "Wage Trends as Performance Displays Productive Potential: A Model and Application to Academic Early Retirement." *The Bell Journal of Economics*, 8, 419-443.

[17] Galindo-Rueda, F. (2003), "Employer Learning and Schooling-Related Statistical Discrimination in Britain." Discussion Paper, IZA.

[18] Gibbons, R. and L. Katz (1991), "Layoffs and Lemons." *Journal of Labor Economics*, 9, 315-389.

[19] Greenwald, B. (1986), "Adverse Selection in the Labour Market." *Review of Economic Studies*, 53, 325-347.

[20] Hansen, K., J. Heckman, and K. Mullen (2004), "The Effect of Schooling and Ability on Achievement Test Scores." *Journal of Econometrics*, 121, 39-98.

[21] Harris, M. and B. Holmstrom (1982), "A Theory of Wage Dynamics." *Review of Economic Studies*, 49, 315-333.

[22] Hu, L. and C. Taber (2005), "Layoffs, Lemons, Race, and Gender." NBER Working Paper.

[23] Johnson, W. (1978), "A Theory of Job Shopping." *The Quarterly Journal of Economics*, 92, 261-277.

[24] Jovanovic, B (1979a), "Job Matching and the Theory of Turnover." *Journal of Political Economy*, 87, 972-990.

[25] Jovanovic, B (1979b), "Firm-specific Capital and Turnover." *Journal of Political Economy*, 87, 1246-1260.

[26] Lang, K (1986), "A Language Theory of Discrimination." *The Quarterly Journal of Economics*, 101, 363-382.

[27] Lange, F. (2006), "The Speed of Employer Learning." *Journal of Labor Economics*, Forthcoming.

[28] Lazear, E (1986), "Raids and Offer Matching." *Research in Labor Economics*, 8, 141-165.

[29] Light, A. and K. McGarry (1998), "Job Change Patterns and the Wages of Young Men." *Review of Economics and Statistics*, 80, 276-286.

[30] Lucas, R. and E. Prescott (1982), "Equilibrium Search and Unemployment." *Journal of Economic Theory*, 2, 188-209.

[31] Lundberg, S. and R. Startz (1983), "Private Discrimination and Social Intervention in Competitive Labor Markets." *American Economic Review*, 73, 340-347.

[32] Ljungqvist, L. and T. Sargent (2000), *Recursive Macroeconomic Theory* Cambridge, MA: MIT Press.

[33] Milgrom, P. and S. Oster (1987), "Job Discrimination, Market Forces, and the Invisibility Hypothesis." *The Quarterly Journal of Economics*, 102, 453-476.

[34] Mincer, J. and B. Jovanovic (1981), "Labor Mobility and Wages." in S. Rosen, eds., *Studies in Labor Markets*, Chicago, IL: University of Chicago Press.

[35] Mortensen, D. (1998), "Specific Capital and Labor Turnover." *The Bell Journal of Economics*, 9, 572-586.

[36] Moscarini, G. (2003), "Skill and Luck in the Theory of Turnover." Working Paper, Yale University.

[37] Neal, D. (1998), "The Link between Ability and Specialization: An Explanation for Observed Correlations between Wages and Mobility Rates." *Journal of Human Resources*, 33, 173-200.

[38] Neal, D. and W. Johnson (1996), "The Role of Premarket Factors in Black-White Wage Differences." *Journal of Political Economy*, 104, 869-895.

[39] Oettinger, G. (1996), "Statistical Discrimination and the Early Career Evolution of the Black-White Wage Gap." *Journal of Labor Economics*, 14, 52-78.

[40] Rodriguez-Planas, N. (2004), "Signaling in the Labor Market: New Evidence on Plant Closings and Layoffs." Working Paper, IZA.

[41] Schonberg, U. (2005), "Testing for Asymmetric Employer Learning." *Journal of Labor Economics*, 25, 651-691.

[42] Spence, A. (1973), "Job Market Signaling." *The Quarterly Journal of Economics*, 87, 355-374.

[43] Topel, R. (1991), "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority." *Journal of Political Economy*, 99, 145-176.

[44] Topel, R. and M. Ward (1992), "Job Mobility and the Careers of Young Men." *The Quarterly Journal of Economics*, 107, 439-479.

[45] Waldman, M. (1984), "Job Assignment, Signaling and Efficiency." *Rand Journal of Economics*, 15, 255-270.

[46] Wilde, L. (1979), "An Information-theoretic Approach to Job Quits." in S. Lippman and J. McCall, eds., *Studies in the Economics of Search*, Amsterdam: North Holland Publishing.

Table 1: Summary Statistics

Variable	Mean	S.D.
Education	13.392	2.402
Black	0.124	0.329
Hispanic	0.061	0.239
Ln(Real hourly wage)	2.556	0.592
Actual experience	7.253	4.763
Job tenure	2.913	3.356
Standardized *AFQT*	0.000	1.000

Source: Author's calculations from NLSY-79.

Note: 1. The sample consists of 4132 individuals with 48617 observations in the years from 1979 to 2000. See the Data section of the paper for details of sample construction.

Table 2: Job Separations and Total Number of Jobs Held During the First 2, 5, and 10 Years of Career

	2 Years		5 Years		10 Years	
	Mean	SD	Mean	SD	Mean	SD
Job separation: 0	0.384	0.486	0.103	0.304	0.032	0.177
Job separation: 1	0.340	0.474	0.190	0.392	0.083	0.277
Job separation: between 2 and 5	0.275	0.446	0.568	0.495	0.460	0.498
Job separation: between 5 and 10	0.001	0.030	0.131	0.337	0.312	0.464
Job separation: greater than 10	0	0	0.008	0.089	0.111	0.315
Job separation: Max	6		19		29	
Job separation: total	1.024	1.068	3.016	2.323	5.568	3.950
Jobs held: total	1.757	1.095	3.733	2.309	6.214	3.927
Number of Observations	4132		4132		4132	

Source: Author's calculation from NLSY-79.

Note: 1. All the estimates are weighted by the NLSY-79 sampling weights.

2. Job separation counts and total number of jobs held are obtained from the NLSY-79 work history file which reports the starting and ending dates for jobs held at the time of each interview and the same information for up to 5 jobs which began and ended since the last interview.

Table 3: Probit Marginal Effects of Standardized AFQT on Job Mobility

	(1)	(2)	(3)	(4)
Standardized *AFQT*	-0.036***	-0.032***	-0.025***	-0.012**
	(0.004)	(0.005)	(0.005)	(0.005)
Standardized *AFQT**Experience/10		0.026***	0.015**	0.014**
		(0.007)	(0.007)	(0.007)
Pseudo R^2	0.004	0.167	0.187	0.189
Number of Observations (Individuals)	48617 (4132)			

Source: Author's calculation from NLSY-79.

Notes: 1. All the probit marginal effects are means of the individual marginal effects.

2. The dependent variable is a dummy variable for at least one job separation during the year. Model (2) also includes experience/10 as independent variable. Model (3) also includes experience/10, black, hispanic, industry and occupation dummies, and year dummies as independent variables. Model (4) includes school enrollment status at the ASVAB test date and highest grade completed at the ASVAB test date as additional independent variables besides the ones in model (3).

3. The standard errors are in parentheses and are White/Huber standard errors accounting for potential correlation at the individual level. The standard errors of the marginal effects are derived through the delta-method. * signifies significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 4: The Effects of Schooling and Standardized *AFQT* on Wages

	OLS		IV	
	(1)	(2)	(3)	(4)
Education	0.066***	0.070***	0.067***	0.074***
	(0.016)	(0.016)	(0.016)	(0.016)
Standardized *AFQT*	0.076***	0.038***	0.072***	0.018
	(0.010)	(0.010)	(0.010)	(0.011)
Education* Experience/10	-0.024*	-0.034***	-0.050***	-0.065***
	(0.012)	(0.013)	(0.018)	(0.018)
Standardized *AFQT** Experience/10		0.052***		0.073***
		(0.011)		(0.011)
R-squared	0.307	0.308	0.302	0.303
Number of Observations (Individuals)	48617 (4132)			

Source: Author's calculation from NLSY-79.

Note: 1. All the estimates are weighted by the sampling weights provided by the NLSY-79.

2. The dependent variable is the natural log of the respondent's hourly wage. All the regressions in the table contain a cubic in experience, black, hispanic, industry and occupation affiliation, year effects, education interacted with year effects, interactions between black and year effects, and between hispanic and year effects.

3. The standard errors are in parentheses and are White/Huber standard errors accounting for potential correlation at the individual level. * signifies significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 5: The Relationship Among Wages, Standardized AFQT, Job Tenure, and Frequency of Job Separations

	(1)	(2)
Standardized *AFQT*	0.036***	0.051***
	(0.010)	(0.013)
Standardized *AFQT** Experience/10	0.048***	0.049***
	(0.014)	(0.014)
Standardized *AFQT** Tenure/10	0.001	0.021
	(0.020)	(0.023)
Frequency of job separations		-0.002***
		(0.001)
Standardized *AFQT**Frequency of job separations		-0.001*
		(0.000)
Standardized *AFQT**Tenure/10*Frequency of job separations		-0.013**
		(0.005)
R-squared	0.326	0.328
Number of Observations (Individuals)	48617 (4132)	

Source: Author's calculation from NLSY-79.

Note: 1. All the estimates are weighted by the sampling weights provided by the NLSY-79.

2. The dependent variable is the natural log of the respondent's hourly wage. All regressions in the table contain a cubic in experience, a cubic in job tenure, black, hispanic, industry and occupation affiliation, year effects, education interacted with experience, education interacted with year effects, interactions between black and year effects, and between hispanic and year effects.

3. The standard errors are in parentheses and are White/Huber standard errors accounting for potential correlation at the individual level. * signifies significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 6: The Effects of Schooling and Standardized AFQT on Wages under Asymmetric Employer Learning

	(1)	(2)
Education	0.069***	0.094***
	(0.016)	(0.017)
Standardized *AFQT*	0.036***	0.033**
	(0.010)	(0.013)
Education* Experience/10	-0.035***	-0.034***
	(0.013)	(0.013)
Standardized *AFQT** Experience/10	0.056***	0.056***
	(0.015)	(0.015)
Education* Tenure/10	0.015	-0.008*
	(0.010)	(0.005)
Standardized *AFQT** Tenure/10	0.017	0.016*
	(0.022)	(0.010)
Frequency of job separations		-0.006***
		(0.004)
Education*Frequency of job separations		-0.001***
		(0.000)
Standardized *AFQT**Frequency of job separations		-0.0009*
		(0.000)
R-squared	0.326	0.329
Number of Observations (Individuals)	48617 (4132)	

Source: Author's calculation from NLSY-79.

Note: 1. All the estimates are weighted by the sampling weights provided by the NLSY-79.

2. The dependent variable is the natural log of the respondent's hourly wage. All regressions in the table contain a cubic in experience, a cubic in job tenure, black, hispanic, industry and occupation affiliation, year effects, education interacted with year effects, interactions between black and year effects, and between hispanic and year effects.

3. The standard errors are in parentheses and are White/Huber standard errors accounting for potential correlation at the individual level. * signifies significance at the 10% level, ** at the 5% level and *** at the 1% level.