Three Essays on Employer Learning and Statistical Discrimination

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(ABSTRACT)

This dissertation consists of three essays studying employer learning and statistical discrimination of young workers in the U.S. labor market. The first chapter outlines the dissertation by discussing the motivations, methods, and research findings.

Chapter two develops a framework that nests both symmetric and asymmetric employer learning, and derives testable hypotheses on racial statistical discrimination under different processes of employer learning. Testing the model with data from the NLSY79, we find that employers statistically discriminate against black workers on the basis of both education and race in the high school market where learning appears to be mostly asymmetric. In the college market, employers directly observe most parts of the productivity of potential employees and learn very little over time.

In chapter three, we investigate how the process of employer learning and statistical discrimination varies over time and across employers. The comparison between the NLSY79 and the NLSY97 cohorts reveals that employer learning and statistical discrimination has became stronger over the past decades. Using the NLSY97 data, we identify three employer-specific characteristics that influencing employer learning and statistical discrimination, the supervisor-worker race match, supervisor's age, and firm size. Black high school graduates face weaker employer learning and statistical discrimination if they choose to work for a black supervisor, work for an old supervisor, or work in a firm of small size.

In the last chapter, we are interested in the associations between verbal and quantitative skills and individual earnings as well as the employer learning process of these two specific types of skills. There exist significant differences in both the labor market rewards and employer learning process of verbal and quantitative skills between high school and college graduates. Verbal skills are more important than quantitative skills for high school graduates, whereas college-educated workers benefit greatly from having high quantitative skills but little from having high verbal skills. In addition, employers directly learn verbal skills and continuously learn quantitative skills in the high school market, but almost perfectly observe quantitative skills in the college market.

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Chapter 1

Introduction

People make hundreds of decisions on the basis of limited information every day, from what to eat for lunch, to what to focus our energy on today, to whether or not to attend the college, to how to select and hire the best job candidate. When hiring, employers do not know the productivity levels of potential employees, particularly those who are fresh in the labor market. Because of the information asymmetry, employers have to rely on the information accumulated from resumes and job interviews to assess the productivity of potential workers. However, a worker's education background and other characteristics observed by employers at the time of initial hire only convey partial information about the worker's productivity level. As the worker spend more time in the labor market, employers will be able to update their expectations based on the richer information that accumulates with experience rather than the limited initial information.

A growing body of literature now studies the role of learning in the labor market. In two landmark articles Farber and Gibbons (1996) and Altonji and Pierret (2001) develop the benchmark employer learning and statistical discrimination model, and provide a way to empirically test for whether employers statistically discriminate on the basis of easily observable characteristics such as education and race. In the model of employer learning and statistical discrimination, employers do not initially observe workers' productivity, but learn about it over time. With only limited information about the productivity of workers, employers make use of some available and relevant information to distinguish among workers at the time of hire. After hire, employers observe worker's job performance, and gradually reduce their reliance on the initial information. Build upon Altonji and Pierret (2001)'s model, subsequent literature further explores the issue of employer learning and statistical discrimination in the labor market.

The model of employer learning and statistical discrimination has broad applicability to many areas of labor economics, such as the studies of statistical discrimination on the basis of race. A useful summary of existing racial discrimination theories in the labor market is given by Lang and Lehmann (2012). Labor market outcomes of black workers, particularly male black workers, are significantly worse than those of white workers. Empirical research documents a remarkable black-white wage gap for male workers, and provides support for the view that labor market discrimination is one important source of the racial wage gap. Racial differences in social-economic background are likely to lead to a black-white gap in the average skills of workers. Because the acquisition of information is costly, a rational employer has strong incentives to use race, along with education and other relevant information, to evaluate the productivity of potential workers even though racial discrimination is against the law. Depending on whether imperfectly informed employers use race as a cheap source of information, race enters the model of employer learning and statistical discrimination differently, and the time path of racial wage gap will shed some light on the issue of statistical discrimination on the basis of race.

The current literature on employer learning addresses the issue of racial statistical discrimination under the basis assumption that employer learning is symmetric, that is, all firms in the labor market share the same information about worker's productivity. However, some studies[1] find empirical evidence in favor of asymmetric learning, that is, current firms have information advantages over outside firms regarding the productivity of young workers. Easily observable characteristics, such as education and race, will have a longer impact on labor market earnings under asymmetric learning than under symmetric learning. Therefore, there will be more scope for statistical discrimination if learning is asymmetric. The fact that current employer learning literature finds little evidence for statistical discrimination on the basis of race may be due to the strong implicit assumption of symmetric learning. Our study fills the gap in the literature by developing a framework that nests both types of employer learning and testing for racial statistical discrimination under different processes of employer learning.

Another main contribution of our study is to provide a complete picture of the employer

[1] Examples of paper providing empirical evidence for asymmetric employer learning include Schonberg (2007) and Pinkston (2009).

learning and statistical discrimination in the U.S. labor market. Specifically, we investigate how the process of employer learning and statistical discrimination varies over time and across employers. Discrimination in the workplace is a serious problem that can be found worldwide. The U.S. government has passed laws that make discrimination illegal, and implemented policies to reduce discrimination and improve the well-being of the disadvantaged. The evolution of the employer learning and statistical discrimination over the past decades provides some insights into the effectiveness of public policy interventions. In addition, understanding how employer learning and statistical discrimination varies across different types of employers has important implications for government policy that aims to reduce discrimination against the disadvantaged groups.

There is an extensive literature devoted to the labor market rewards of general cognitive ability, however, the contribution of specific types of ability to the earning of young workers is relatively under-researched. We also add to the literature by analyzing the role of two specific types of abilities, verbal and quantitative abilities, in wage determination and exploring the employer learning process of these two types of abilities. Verbal and quantitative abilities are key components of cognitive ability, and are expected to play a vital part in the labor market outcomes of young workers. Learning the labor market rewards and employer learning process of verbal and quantitative abilities are important for both economists and policy makers. It enhances economist's understanding of wage determination, and helps policy makers to better evaluate and design training programs that target for improving the basic skills of low-skilled workers.

This dissertation consists of three important parts studying employer learning and statistical discrimination in the U.S. labor market. Chapter 2 set out a framework that nests both symmetric and asymmetric employer learning, and derives empirically testable hypotheses on statistical discrimination on the basis of race under both types of learning. In chapter 3, we study how the process of employer learning and statistical discrimination varies over time and across employers to gain further insight. Our focus of attention changes from general ability to two specific types of abilities, verbal and quantitative abilities, in chapter 4. We investigate labor market rewards of verbal and quantitative abilities as well as the corresponding employer learning process.

Combining elements of both employer learning and statistical discrimination theories, chapter 2 develops a framework that nests both symmetric and asymmetric employer learning, and derives testable hypotheses on racial statistical discrimination under different processes of employer learning. Testing the model with data from the NLSY79, we find that employers statistically discriminate against black workers on the basis of both education and race in the high school market where learning appears to be mostly asymmetric. In the college market, employers directly observe most parts of the productivity of potential employees and learn very little over time. We conduct a series of sensitivity tests, and find further support for our research findings.

Chapter 3 investigates how the process of employer learning and statistical discrimination varies over time and across employers. We test the hypothesis of employer learning and statistical discrimination with both the NLSY79 and NLSY97 data, and take a further look at the employer learning and statistical discrimination process of black high school graduates in the NLSY97. The comparison between these two cohorts reveals that employer learning and statistical discrimination has became stronger over the past decades. Furthermore, we identify three employer-specific characteristics that influencing employer learning and statistical discrimination, the supervisor-worker race match, supervisor's age, and firm size. Black high school graduates face weaker employer learning and statistical discrimination if they choose to work for a black supervisor, work for an old supervisor, or work in a firm of small size.

In chapter 4, we are interested in the associations between verbal and quantitative skills and individual earnings as well as the employer learning process of these two specific types of skills. Using the NLSY79 data, we find that quantitative skills have a larger impact on wages compared with verbal skills even though both types of skills are important determinants of earnings. In the labor market, employers directly learn workers' verbal skills but gradually learn their quantitative skills. However, there exist significant differences in both the labor market rewards and employer learning process of verbal and quantitative skills between high school and college graduates. Verbal skills are more important than quantitative skills for high school graduates, whereas college-educated workers benefit greatly from having high quantitative skills but little from having high verbal skills. In addition, employers directly learn verbal skills and continuously learn quantitative skills in the high school market, but almost perfectly observe quantitative skills in the college market.

Chapter 2

Testing for Statistical Discrimination with Asymmetric Employer Learning

(ABSTRACT)

This chapter combines elements of both employer learning and statistical discrimination theories to develop a learning-based racial statistical discrimination model. We develop a framework that nests both symmetric and asymmetric employer learning, and derive testable hypotheses on racial statistical discrimination under different processes of employer learning. Testing the model with data from the NLSY79, we find that employers statistically discriminate against black workers in the high school market where learning appears to be mostly asymmetric. In the college market, employers directly observe most of the productivity of potential employees and learn very little over time. A series of sensitivity tests provide further support for our main findings.

2.1 Introduction

In a world where the productivity of labor force participants is difficult to directly observe, employers have to rely on some observable characteristics to infer the unobservable productivity of potential employees. When hiring, employers could only use information contained in resumes, letters of recommendation and job interviews to evaluate workers' productivity. As workers start to work, new information about their performances become available, and employers could learn about their productivity from newly acquired information. The employer learning literature has confirmed that employers make use of some easily observable characteristics, such as education, to distinguish among inexperienced workers at the time of hire, and their pay will depend more on productivity as they accumulate more information.

Some questions arise naturally from the employer learning process. Do employers statistically discriminate against blacks if black workers belong to a group with lower average productivity? Is the process of employer learning that takes place after hiring symmetric or asymmetric? This chapter attempts to provide an answer to these two questions.

There is an extensive literature on the issue of racial statistical discrimination. Empirical research on racial wage gap documents a notable black-white wage gap for male workers. Lang and Manove (2011) find that a substantial racial wage gap emerges when controlling for AFQT score and education, and this wage gap could not be explained by the differences in the quality of schools attended by blacks and by whites. Their findings support the view that statistical discrimination is one source of the black-white wage gaps. On the theoretical side, statistical discrimination models[1] are developed to explore the implications of imperfect information about workers' productivity. The crucial assumption in statistical discrimination literature is that imperfectly informed employers rationally use race to infer workers' productivity.[2]

This chapter aims to test for statistical discrimination on the basis of race from the perspective of employer learning. We combine elements of both employer learning and statistical discrimination theories to formulate a learning-based racial statistical discrimination model. Our model borrows insights from statistical discrimination literature, and assumes that the average productivity of black workers is lower than that of white workers.[3] Racial statistical discrimination arises because employers know the average productivity differences. Race is

[1]There are two main branches of statistical discrimination literature, screening discrimination models and rational stereotyping models. The former, originated from Phelps (1972), attribute discriminatory outcomes to differential observability of productivity. One the other hand, rational stereotyping models that originated from Arrow (1973) assume that employer's negative beliefs about the quality of black workers are self-fulfilling. See Lang and Lehmann (2012) for a good summary of race discrimination theories in the labor market.

[2]In taste-based discrimination models, employers have prejudice against black workers.

[3]This version of statistical discriminaiton is discussed in Phelps (1972) and Aigner and Cain (1977). Two groups differ with respect to the average productivity but not with respect to the variance of error term. Sattinger (1998) is an example that builds on an extension to this version of statistical discriminaiton. Workers are assumed to be homogenous in productivity, but their quitting behaviors differ across groups. One group has a greater proportion of workers whose quit-rate is high. Firms observe quit rates imperfectly and thus rationally set unequal employment criteria or unequal interview rates.

a correlate of productivity, and thus is incorporated into the employer learning model. It could work as either an easy-to-observe variable or a hard-to-observe variable depending on whether or not employers initially rely on it to predict productivity.

Our learning-based racial statistical discrimination model is built on the benchmark employer learning model developed by two landmark articles, Farber and Gibbons (1996) and Altonji and Pierret (2001).[4] Altonji and Pierret (2001) establish the model of employer learning and statistical discrimination, and much of the subsequent literature on employer learning is guided by the framework set out in this influential study. Many recent studies provide empirical evidence for this model, and further find that the employer learning process differs across educational groups.

Some studies on employer learning also address the issue of racial statistical discrimination,[5] but all these studies are carried out under the assumption that employer learning is symmetric, that is, both current and outside firms share the same information about workers' productivity. Earlier literature on employer learning usually builds around the assumption of symmetric learning, however, the empirical studies on whether learning is symmetric or asymmetric so far fail to reach a consensus.

Another main contribution of this chapter is to distinguish between symmetric and asymmetric learning in the labor market and address the issue of racial statistical discrimination under each scenario. To the best of my knowledge, there are no studies investigating learning-based racial statistical discrimination under asymmetric learning. The nature of employer learning has great influence on racial statistical discrimination. If learning is asymmetric, there might be more scope for racial statistical discrimination. The chapter attempts to fill the gap in the current employer learning literature by developing a testable model that nests both learning hypotheses and testing for racial statistical discrimination. We build on some previous work, particularly Altonji and Pierret (2001) and Lange (2007), set up a framework that nests both learning hypotheses, and propose a new way to distinguish between two types of employer learning. More specifically, we differentiate between general experience and job tenure to explore whether employer learning is symmetric or asymmetric. Symmetric learning implies a continuous learning process over a worker's general experience. If employer learning is asymmetric, however, the learning process should mainly take place

[4] Farber and Gibbons (1996) develop their empirical predictions for wage levels while Altonji and Pierret (2001) work with log wages.

[5] See Altonji and Pierret (2001), Arcidiacono, Bayer, and Hizmo (2010) and Mansour (2012).

over the job tenure rather than general experience.

In this chapter, we use the 2008 release of National Longitudinal Survey of Youth 1979 (NLSY79) to test racial statistical discrimination and to distinguish between two types of employer learning. After confirming Altonji and Pierret (2001)'s finding of employer learning and statistical discrimination on the basis of education, we conduct the empirical analysis for the full sample and two educational groups, high school graduates and college graduates.[6] For the full sample, we could not draw any definite conclusion because the empirical analysis gives conflicting results. The results for high school graduates provide evidence in favor of racial statistical discrimination and asymmetric learning. On the other hand, the college sample reveals a distinct pattern of employer learning. In the college market, the key aspects of productivity are directly observed upon initial entry and thus little learning takes place subsequently, supporting the main findings reported in Arcidiacono, Bayer, and Hizmo (2010). A series of sensitivity tests demonstrate that our main results are robust to alternative explanation of the data. The employer learning process for high school graduates tends to be more like purely asymmetric, and the racial wage gap can not be attributed to racial differences in match quality or the skill level of jobs.

The structure of this chapter is as follows. Section 2 describes the learning-based racial statistical discrimination model, and derives empirically testable predictions under different scenarios. Section 3 gives an overview of the data and empirical specifications applied in the empirical analysis. The estimation results are reported in Section 4, and Section 5 checks their robustness to alternative interpretations. Section 6 concludes and discusses future work.

2.2 The Learning-based Racial Statistical Discrimination Model

In this section, we develop a learning-based racial statistical discrimination model, and derive testable predictions under different assumptions. Much of the model is based on Altonji and Pierret (2001) and Lange (2007). Altonji and Pierret (2001) first propose the theory of employer learning and statistical discrimination, and their framework is widely applied in

[6]The employer learning literature (e.g., Arcidiacono, Bayer, and Hizmo (2010)) finds that different educational groups are likely to be associated with distinct patterns of employer learning.

the employer learning literature. Lange (2007) builds on Altonji and Pierret (2001) and constructs a framework to formally estimate the speed of employer learning.

The model developed in this section examines the time trend of wage coefficients on correlates of productivity to test whether or not employers statistically discriminate against black workers, and also provides predictions that could distinguish between symmetric and asymmetric learning.

2.2.1 The Employer Learning Model

Suppose workers first enter the labor market at time $t = 0$ and stay with their first employers during the time period t under consideration.

Following the standard literature, we specify that worker i's log productivity at time t_i depends linearly on a set of variables (s_i, q_i, z_i, η_i) and a polynomial in time $\tilde{H}(t_i)$:

$$\begin{aligned}\chi_{i,t} &= \tilde{\chi}(s_i, q_i, z_i, \eta_i) + \tilde{H}(t_i) \\ &= \gamma s_i + \alpha q_i + \lambda z_i + \eta_i + \tilde{H}(t_i).\end{aligned} \tag{2.1}$$

The variables s_i represent the information available to both employers and researchers, such as education. The variables q_i describe the information available to employers but not used or observed by researchers, such as information obtained through job interviews. The variables z_i are correlates of productivity that are available to researchers but not to employers. Much of the literature assumes that AFQT score is such a correlate of productivity, and we also make this assumption. The variables z_i are normalized so that all the elements of λ are positive. The variables η_i denote the information that is unobserved by both employers and researchers. Finally, $\tilde{H}(t_i)$ denotes the relation between log productivity and time, and is assumed to be independent of (s_i, q_i, z_i, η_i). Therefore, human capital accumulation is incorporated into the model through experience profiles of productivity, $\tilde{H}(t_i)$, but is assumed to have no influence on the time paths of the impacts of s_i and z_i on log productivity. The variation of the time gradient of log wages with s_i and z_i is interpreted as the outcome of an employer learning process about workers' productivity. The subscript i will be suppressed from now on. The race information enters into the model differently depending on whether or not employers rely on race to evaluate workers' productivity. In the following sections, we will discuss these two cases respectively.

No Statistical Discrimination by Race

If employers obey the law and do not use race as information, then the information used by employers at time $t = 0$ is (s, q). The black indicator $Black$, which takes 1 if the worker is black and 0 otherwise, can be thought of as a component of the correlates of productivity z, which is unobservable to employers.

Employers observe (s, q) but not (z, η), and form the conditional expectation of (z, η) on the information available. We assume that (s, q, z, η) are jointly normally distributed. Although employers can not directly observe z, it is assumed that $\overline{z} = E(z|s, q)$ is common knowledge. Employers use the average information to predict z by the following linear relation:

$$z = E(z|s, q) + \nu = \overline{z} + \nu. \tag{2.2}$$

Because of the normality assumption the expectation of η conditional on (s, q) is also linear in (s, q):[7]

$$\eta = E(\eta|s, q) + e = \alpha_1 s + e. \tag{2.3}$$

Substituting (2.2) and (2.3) in (2.1), we can express the initial log productivity as a liner function of the information available to employers at time $t = 0$:

$$\begin{aligned} \chi &= (\gamma + \alpha_1)s + \alpha q + \lambda\overline{z} + \lambda\nu + e + \tilde{H}(0) \\ &= E[\tilde{\chi}|s, q, \overline{z}] + (\lambda\nu + e) + \tilde{H}(0). \end{aligned} \tag{2.4}$$

As workers accumulate more labor market experience, new information about worker's job performance become available to employers. In each period, employers obtain a noisy signal y_t of $\tilde{\chi}$:

$$y_t = \tilde{\chi} + \epsilon_t, \tag{2.5}$$

where the noise ϵ_t is assumed to be uncorrelated with all other variables and is independently, identically and normally distributed with a variance of σ_ϵ^2. At time t, employers could observe a t dimensional vector of measurements, $Y^t = (y_1, \ldots, y_t)$.

[7] We define η and coefficient α on q in (2.1) so that the mean of η does not depend on q.

The normality assumption simplifies the process of updating employer expectations about $\tilde{\chi}$. When workers enter the labor market for the first time, that is, at time $t = 0$, the prior mean of employers' beliefs about $\tilde{\chi}$ is

$$\mu_0 = E[\tilde{\chi}|s, q, \overline{z}] = (\gamma + \alpha_1)s + \alpha q + \lambda \overline{z}. \tag{2.6}$$

After hiring, employers receive a signal of worker's log productivity y_t and update their beliefs each time period. Assume that the variance of $\tilde{\chi}$ conditional on initial information $(s, q, \overline{z})$ is σ_0^2, the variance of the initial expectation error $(\lambda\nu + e)$. Because of the normality assumption, the posterior distribution of employers' beliefs about $\tilde{\chi}$ at time t is normal with mean μ_t and variance σ_t^2,

$$\begin{aligned}\mu_t = E[\tilde{\chi}|s, q, \overline{z}, Y^t] &= \frac{\sigma_\epsilon^2}{t\sigma_0^2 + \sigma_\epsilon^2}\mu_0 + \frac{t\sigma_0^2}{t\sigma_0^2 + \sigma_\epsilon^2}\left(\frac{1}{t}\sum_{t=1}^{t} y_t\right) \\ &= (1 - \theta_t)\,\mu_0 + \theta_t\left(\frac{1}{t}\sum_{t=1}^{t} y_t\right)\end{aligned} \tag{2.7}$$

where

$$\theta_t = \frac{t\sigma_0^2}{t\sigma_0^2 + \sigma_\epsilon^2} \tag{2.8}$$

and

$$\sigma_t^2 = \frac{\sigma_0^2\sigma_\epsilon^2}{t\sigma_0^2 + \sigma_\epsilon^2}. \tag{2.9}$$

The learning parameter θ_t lies in the interval $[0, 1]$, and converges from 0 to 1 as t increases. Therefore, the expected log productivity of a worker at time t is

$$E[\chi|s, q, \overline{z}, Y^t] = (1 - \theta_t)\,\mu_0 + \theta_t\left(\frac{1}{t}\sum_{t=1}^{t} y_t\right) + \tilde{H}(t). \tag{2.10}$$

Employers set the wage equal to the expected productivity conditional on the information available $(s, q, \overline{z}, Y^t)$:

$$W(s, q, \overline{z}, Y^t) = E\left[exp\left(\chi\right)|s, q, \overline{z}, Y^t\right]. \tag{2.11}$$

Because of the normality assumption, the distribution of χ conditional on $(s, q, \overline{z}, Y^t)$ is normal. We use the property of a log normal distribution, and define $H(t) = \tilde{H}(t) + \frac{1}{2}\sigma_t^2$.[8] Using equation (2.11) and taking logs, we obtain the following expression for log wages:

$$w(s, q, \overline{z}, Y^t) = (1 - \theta_t)\,\mu_0 + \theta_t\left(\frac{1}{t}\sum_{t=1}^{t} y_t\right) + H(t). \tag{2.12}$$

Equation (2.12) gives the log wages conditional on the information available to employers $(s, q, \overline{z}, Y^t)$. However, researchers observe $(s, z, \overline{z}, t)$ instead of $(s, q, \overline{z}, Y^t)$, and we need to express the log wages as a function of information available to researchers. We define the linear projections of (q, η):

$$q = \gamma_1 s + u_1 \tag{2.13}$$
$$\eta = \gamma_2 s + u_2. \tag{2.14}$$

Therefore, the linear projection of log wages conditional on information available to researchers, $(s, z, \overline{z}, t)$, is given by

$$\begin{aligned} w_t &= E^*\left[w\left(s, q, \overline{z}, Y^t\right)|s, z, \overline{z}, t\right] \\ &= (1 - \theta_t)\,E^*\left[\mu_0|s, z, \overline{z}, t\right] + \theta_t E^*\left[\tilde{\chi}|s, z, \overline{z}, t\right] + H(t). \end{aligned} \tag{2.15}$$

Equations (2.6) and (2.13) imply

$$E^*[\mu_0|s, z, \overline{z}, t] = \lambda\overline{z} + (\gamma + \alpha\gamma_1 + \alpha_1)s, \tag{2.16}$$

and equations (2.1), (2.13) and (2.14) imply

$$E^*[\tilde{\chi}|s, z, \overline{z}, t] = \lambda z + (\gamma + \alpha\gamma_1 + \gamma_2)s. \tag{2.17}$$

[8] $E\left[exp\left(\chi\right)|s, q, \overline{z}, Y^t\right] = exp\left(E\left[\chi|s, q, \overline{z}, Y^t\right] + \frac{1}{2}\sigma_t^2\right) = exp\left(E\left[\tilde{\chi}|s, q, \overline{z}, Y^t\right] + \tilde{H}(t) + \frac{1}{2}\sigma_t^2\right)$. The expectation error at time t does not depend on $(s, q, \overline{z}, Y^t)$, so $\frac{1}{2}\sigma_t^2$ is constant with respect to $(s, q, \overline{z}, Y^t)$.

Substituting (2.16) and (2.17) into (2.15) and rearranging terms results in

$$w_t = \lambda \left\{ (1-\theta_t)\, \overline{z} + \theta_t z \right\} + \chi_t s + H(t) \tag{2.18}$$

where

$$\chi_t = (1-\theta_t)(\gamma + \alpha\gamma_1 + \alpha_1) + \theta_t(\gamma + \alpha\gamma_1 + \gamma_2). \tag{2.19}$$

The weights that employers place on $\overline{z}$ and z are given by $(1-\theta_t)$ and θ_t, respectively. The learning parameter θ_t reflects the process of employer learning.

If there is no statistical discrimination on the basis of race, employers do not rely on race to predict the productivity of new workers. However, productivity differences do exist among different racial groups. Therefore, we assume that the correlates of productivity z consists of two components, AFQT score and black indicator *Black*. The correlates of productivity z can be expressed as

$$z = \tau_1 AFQT + \tau_2 Black. \tag{2.20}$$

Most literature assumes that AFQT score is a positive correlate of productivity, and we assume that as well. In the NLSY79 sample, the mean of the standardized AFQT score for blacks is about one standard deviation below the mean for whites. The fact that the average productivity of black workers is lower than that of white workers implies that the black indicator *Black* is negatively correlated with the productivity. Hence, $\tau_1 > 0$ and $\tau_2 < 0$.

Plugging (2.20) into (2.18), the wage equation can be rewritten as

$$w_t = \theta_t\{\lambda\tau_1 AFQT + \lambda\tau_2 Black\} + \chi_t s + other \tag{2.21}$$

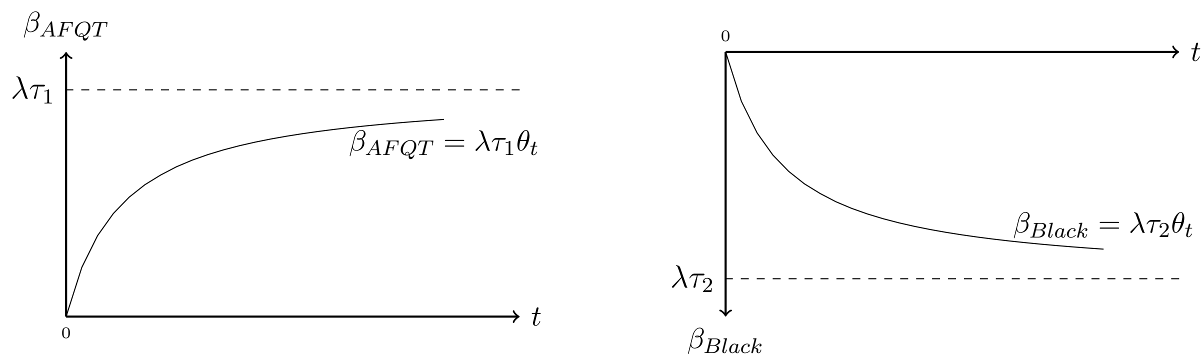
where

$$other = H(t) + \lambda(1-\theta_t)\overline{z}. \tag{2.22}$$

The learning parameter θ_t equals 0 at the time of initial hire, and converges to 1 over time. Therefore, equation (2.21) implies that, as time passes, the coefficient on the positive correlate of productivity $AFQT$ increases from 0 to $\lambda\tau_1$ and the coefficient on $Black$ decreases from 0 to $\lambda\tau_2$ since $\lambda\tau_1 > 0$ and $\lambda\tau_2 < 0$. The time paths of the coefficients on $AFQT$ and $Black$ are shown in Figure 2.1. This is the basis for Proposition 1.

Proposition 1 *In the case of no racial statistical discrimination, the coefficient on Black is initially* 0 *and decreasing in* t*.*

Figure 2.1: No Racial Statistical Discrimination



Panel A. The coefficient on $AFQT$

Panel B. The coefficient on $Black$

Statistical Discrimination by Race

If employers know the average productivity of each race group and use race as a cheap source of information, then they will statistically discriminate against black workers at the time of initial hire. In this case, the black indicator $Black$ acts as an easily observable variable to employers. The information available to employers at time $t = 0$ is $(s, q, Black)$, and the black indicator $Black$ enters into our model by the following linear relation:[9]

$$z = E(z|s, q, Black) + \nu = \overline{z} + \delta Black + \nu \tag{2.23}$$

where $\delta < 0$ resulting from the fact that black workers are associated with lower average productivity. Employers know the average differences between blacks and whites, and hence $E(z|s, q, Black)$ is written as a function of $\overline{z}$ and $Black$.

[9] One implicit assumption is that the signals of different racial groups are equally informative, that is, $\sigma_{\epsilon B} = \sigma_{\epsilon W} = \sigma_{\epsilon}$. Many statistical discrimination models build around the crucial assumption that the signals employers receive from black workers are noisier than that from white workers. In our model, statistical discrimination arises because of the assumption that the average productivity of black workers is lower than that of white workers.

Employers make use of racial information to predict workers' productivity, so *Black* is no longer a component of the hard-to-observe correlates of productivity z. z can be expressed as

$$z = \tau_3 AFQT \tag{2.24}$$

where $\tau_3 > 0$ because AFQT score is positively correlated with productivity.

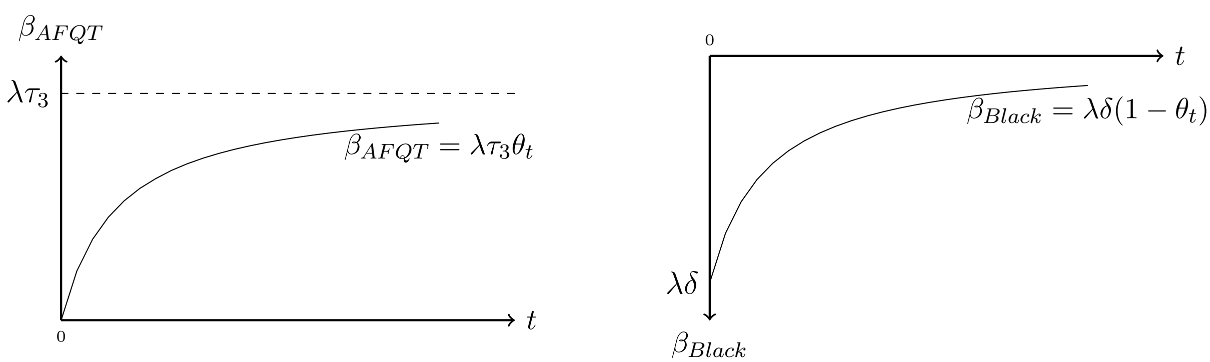
Using (2.23) and (2.24), we obtain the following wage equation:

$$w_t = \{\theta_t \lambda \tau_3 AFQT + (1 - \theta_t)\, \lambda \delta Black\} + \chi_t s + other. \tag{2.25}$$

The learning parameter θ_t is bounded between 0 and 1, and increases to 1 as worker's career progresses. Hence, the equation (2.25) implies that, as employers learn over time, the coefficient on $AFQT$ increases from 0 to the positive value $\lambda\tau_3$, while the coefficient on $Black$ rises to 0 from the initially negative value $\lambda\delta$. The time paths of the coefficients on $AFQT$ and $Black$ are shown in Figure 2.2. Proposition 2 summarizes this implication.

Proposition 2 *In the case of racial statistical discrimination, the coefficient on Black is initially negative and increasing in t.*

Figure 2.2: Racial Statistical Discrimination



Panel A. The coefficient on *AFQT*

Panel B. The coefficient on *Black*

2.2.2 Symmetric Learning

The benchmark employer learning model developed by Farber and Gibbons (1996) and Altonji and Pierret (2001) assumes that employer learning is symmetric, that is, all firms share the same information about workers' productivity. If employer learning is symmetric, both current firms and outside firms learn about workers' productivity over time, and thus the employer learning process occurs over workers' general labor market experience. We will derive the implications of symmetric learning first, and then move on to the case of asymmetric learning.

We use X to denote workers' general experience and T to denote workers' job tenure with a specific firm. It is worth noting that the theory of human capital also distinguishes between two types of experience, general experience and firm-specific experience.[10] The employer learning theory differs from the human capital theory in the sense that it focuses on the time paths of the effects of easy-to-observe and hard-to-observe variables on productivity.

Consider the case where a worker changes n jobs in his lifetime. The lengths of job tenure for each job are $T_1, T_2, \ldots, T_n$, and $T_1 + T_2 + \cdots + T_n = a$, where a is the length of general experience for this worker. At time $t = T_1$, the worker moves to a new job, and accumulates T_1 units of general experience and 0 unit of tenure with his new employer. At time $t = T_1 + T_2$, the worker has spent T_2 units of time on his new job, and gains $T_1 + T_2$ units of general experience and T_2 units of tenure. The time paths of the learning parameter θ_t over general experience X and over tenure T are shown in Figure 2.3 where we assume $n = 3$ to simplify the matter.

When the worker's career starts at time $t = 0$, the learning parameter $\theta_t(t = 0)$ equals 0. At that time, the worker has zero working experience, so $\theta^X(X = 0) = \theta_t(t = 0) = 0$. Whenever the worker makes a move, his tenure with the new employer becomes zero, and $\theta^T(T = 0) >= \theta_t(t = 0) = 0$. For example, the worker has T_1 units of general experience when he starts a new job at $t = T_1$, and $\theta^T(T = 0) = \theta^X(X = T_1) > 0$ as shown in Figure 2.3. Therefore, $0 = \theta^X(X = 0) \leq \theta^T(T = 0)$.

Because $\theta_t' = \frac{\sigma_0^2\sigma_\epsilon^2}{(\sigma_0^2 t+\sigma_\epsilon^2)^2} > 0$ and $\theta_t'' = \frac{-2\sigma_0^4\sigma_\epsilon^2}{(\sigma_0^2 t+\sigma_\epsilon^2)^3} < 0$, the learning parameter θ_t increases at a decreasing rate, implying that the speed of employer learning declines over time. We use K to denote the speed of employer learning, and conclude that the speed of learning over general experience, K^X, is faster than that over tenure, K^T.[11]

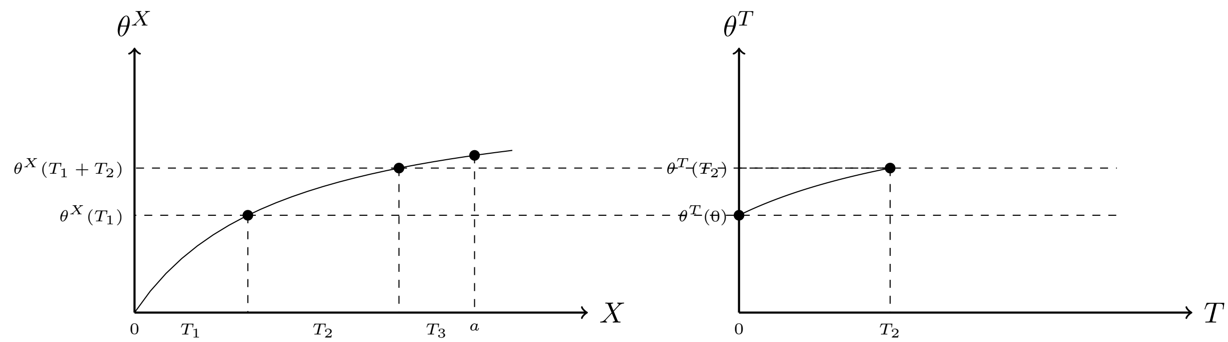
Proposition 3 *In the case of symmetric learning, the initial learning parameter θ_t over*

[10]Human capital theory argues that general experience increases worker's productivity in both the current firm and outside firms but firm-specific experience only increases worker's productivity in the current firm.

[11]One exception is that the worker stays with one firm in his entire career life. In that case, the speed of employer learning over general experience equals that over tenure.

general experience is not greater than that over tenure, and the speed of employer learning is faster over general experience than that over tenure.

Figure 2.3: Symmetric Learning



Panel A. The time path of θ over Experience

Panel B. The time path of θ over Tenure

The time path of the coefficients on $AFQT$ shown in Panel A of Figure 2.1 and Figure 2.2, $\beta_{AFQT} = \lambda\tau_*\theta_t$ where $\lambda > 0$ and $\tau_* > 0$,[12] is entirely determined by the learning parameter θ_t. The learning parameter θ_t gradually rises from 0 to 1 as employers updating their expectations about workers' productivity. From Proposition 3, we derive the following predictions about the coefficients on $AFQT$.

1. The initial coefficient on $AFQT$ using general experience measure is not greater than that using tenure measure, that is, $0 = \beta^X_{AFQT}(X=0) \leq \beta^T_{AFQT}(T=0)$.
2. The coefficient on $AFQT$ increases over time, so $K^X_{AFQT} > K^T_{AFQT} > 0$.

The variation of the coefficient on black indicator *Black* depends on whether race acts as an easy-to-observe variable such as eduction or as an hard-to-observe variable such as AFQT score. If employers use race as information to predict productivity, *Black* enters into the employer learning model as an hard-to-observe variable, and the learning-based racial statistical discrimination model developed in this chapter predicts a narrowing racial wage gap. In contrast, if employers do not rely on racial information, *Black* can be understood as an easy-to-observe variable, and we expect a widening racial wage gap.

[12]If employers do not statistically discriminate against black workers, then $\beta_{AFQT} = \lambda\tau_1\theta$. However, if statistical discrimination on the basis of race does exist in the labor market, then $\beta_{AFQT} = \lambda\tau_3\theta$. As discussed earlier, both τ_1 and τ_3 are positive.

If employers obey the law, and do not take racial information into consideration when evaluating a worker's productivity, then the time path of the coefficient on *Black* is $\beta_{Black} = \lambda\tau_2\theta_t$ where $\tau_2 < 0$ reflecting the negative correlation between *Black* and productivity. Proposition 1 and Proposition 3 leads to the following implications about the coefficient on *Black*.

1. The initial coefficient on *Black* is zero using general experience measure, and zero or negative using tenure measure. That is, $0 = \beta^X_{Black}(X = 0) \geq \beta^T_{Black}(T = 0)$.

2. The coefficient on *Black* declines over time, so $K^X_{Black} < K^T_{Black} < 0$.

If statistical discrimination on the basis of race does exist in the labor market, the time path of the coefficient on *Black* is $\beta_{Black} = \lambda\delta(1 - \theta_t)$ where $\lambda > 0$ and $\delta < 0$. Proposition 3 implies that $1 - \theta^X(X = 0) \geq 1 - \theta^T(T = 0) > 0$. Moreover, the learning parameter θ_t is increasing in t, so the weight on *Black*, $(1 - \theta_t)$, is declining over time. The predictions derived from Proposition 2 and Proposition 3 are as follows.

1. The initial coefficient on *Black* using general experience is at least as negative as that using tenure, that is, $\beta^X_{Black}(X = 0) \leq \beta^T_{Black}(T = 0) < 0$.

2. The coefficient on *Black* increases over time, so $K^X_{Black} > K^T_{Black} > 0$.

2.2.3 Asymmetric Learning

Many recent studies (Bauer and Haisken-DeNew (2001), Schonberg (2007), Pinkston (2009)) find empirical evidence in favor of asymmetric employer learning, that is, current firms accumulate more information about the productivity of their workers than do outside firms. If employer learning is asymmetric, the learning process mainly takes place over tenure.[13] As workers spend more time in the workplace, current firms observe their performances and update expectations while outside firms are insulated from the employer learning process. The workers' job performance information is only available to their current firms.

Consider a worker with a units of general experience. If the worker changes n firms, then the length of his general experience X is the sum of his tenure with each firm, that is, $X = T_1 + T_2 + \cdots + T_n = a$. If the worker does not switch job at all and stays with one firm,

[13] Here we discuss the case where employer learning is pure asymmetric. In the section of robustness check, we examine the possibility that employer learning is imperfect asymmetric rather than pure asymmetric.

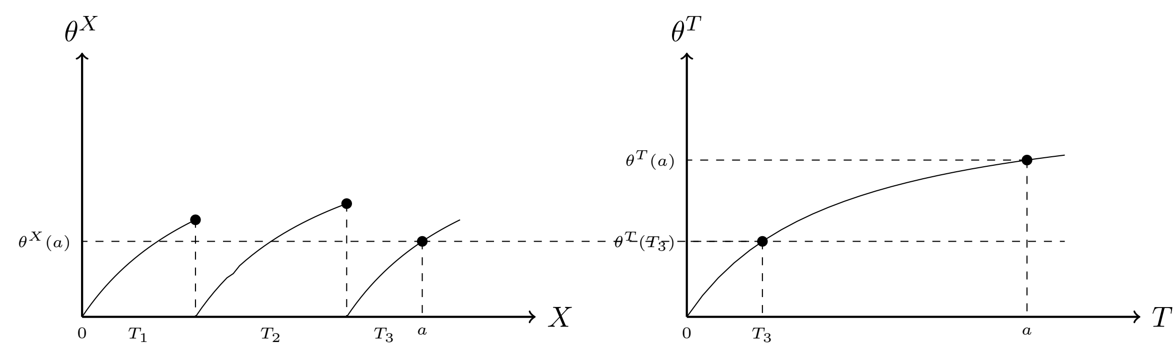
then the length of his general experience X is the same as that of tenure, that is, $X = T = a$. The time paths of the learning parameter θ_t over general experience X and over tenure T are shown in Figure 2.4 where we assume again that the worker switches job 3 times during the time period under consideration.

Because employer learning process only happens over job tenure, the learning parameter θ_t equals zero whenever the worker moves to a new firm, that is, $\theta^T(T = 0) = 0$. When the worker initially enters the labor market and begins his first job at time $t = 0$, both his general experience and tenure equal zero, so $\theta^X(X = 0) = \theta^T(T = 0) = 0$.

In the case of asymmetric learning, outside firms have no access to the rich information on workers' job performance in other firms, so employer learning process starts all over again whenever the worker makes a job change. Given a specific time period, therefore, the speed of employer learning is faster over tenure than over general experience, that is, $K^X < K^T$. As shown in Figure 2.4, $\theta^X(X = a) = \theta^T(T = T_3) < \theta^T(T = a)$. Moreover, $K^X = 0$ whenever the worker moves to a new firm.

Proposition 4 *In the case of asymmetric learning, the initial learning parameter θ_t over general experience is the same as that over tenure, and the speed of employer learning is slower over general experience than that over tenure.*

Figure 2.4: Asymmetric Learning



Panel A. The time path of θ over Experience Panel B. The time path of θ over Tenure

We could derive the following predictions from Proposition 1, 2 and 4.

1. The initial coefficients on $AFQT$ and $Black$ are the same either we use general experience or tenure as the time measure. That is, $\beta^X_{AFQT}(X = 0) = \beta^T_{AFQT}(T = 0) = 0$, and $\beta^X_j(X = 0) = \beta^T_j(T = 0)$.

2. The coefficient on $AFQT$ always increases over tenure, and the speed of employer learning is faster using tenure than using experience, that is, $0 \leq K^X_{AFQT} < K^T_{AFQT}$.

3. If employers do not statistically discriminate against black workers, the coefficient on *Black* is initially zero and decreasing over tenure. That is, $\beta^X_{Black}(X = 0) = \beta^T_{Black}(T = 0) = 0$ and $0 \geq K^X_{Black} > K^T_{Black}$.

4. In the case of statistical discrimination on the basis of race, the coefficient on *Black* is initially negative and increasing over tenure. That is, $\beta^X_{Black}(X = 0) = \beta^T_{Black}(T = 0) < 0$ and $0 \leq K^X_{Black} < K^T_{Black}$.

2.3 Data and Empirical Specification

2.3.1 Data: NLSY79

The empirical analysis is based on the 2008 release of National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and are then interviewed on a biennial basis. The NLSY data contain detailed information on family background, academic performance and labor market outcomes of a cohort of young workers for whom the employer learning should matter the most, and its weekly work history data provide the information needed for accurate measurements of both general experience and job tenure.

In selecting the sample, we follow the criteria used in Altonji and Pierret (2001) and Arcidiacono, Bayer, and Hizmo (2010). The empirical analysis is restricted to black and white male workers who have completed at least 9 years of education. We focus exclusively on male workers because the analysis of female workers involves selection issues. We only consider observations after the respondent has made the school-to-work transition. A respondent is considered to have entered the labor market when he has left school for the first time, which is defined as the year of the last enrollment in regular school. Potential experience is the sum of months since the respondent first left school.

For each respondent, we construct monthly labor market history from the work history data, which contains respondent's week-by-week labor force status. Each respondent's weekly work records are transformed into monthly ones. We link all the jobs across different survey years and build a complete employment history for each respondent in the sample. Multiple jobs held at the same time are treated as a new job, and the average wage is used as the wage for the newly constructed job. We use the hourly rate of pay for each job and the hours per week worked for each job to calculate the average wage. The deflators from CPI-U released by Bureau of Labor Statistics are used to create real hourly wage with 1990 as the base year, and all observations with real wages less than \$1 or more than \$100 are excluded from the analysis. From the monthly work history data, we construct measures of job tenure and general actual experience. Tenure is computed as the number of months between the start of the job and either the date the job ended or the interview date, and general actual experience is calculated as the sum of tenure for each job.[14]

Following the literature, we use Armed Forces Qualification Test (AFQT), which is administered to the NLSY respondents, as our measure of productivity. The AFQT score provides a summary measure for basic literacy and numeric skills and is thus widely used as a correlate of productivity. To make our measure of productivity comparable to other studies, we standardize the AFQT score to have a zero mean and a standard deviation of one for each three-month age cohort.[15] The education variable is defined as the highest grade completed by the respondent at the time of interview. In the empirical analysis, we give special attention to two educational groups, high school graduates and college graduates. High school graduates are defined as workers who have completed 12 years of schooling at the interview date, and college graduates are workers who have at least 16 years of schooling.

Table 2.1 presents the summary statistics for the NLSY79 sample used in the analysis.[16] It is worth noting that the average AFQT score of black workers is about one standard deviation lower than that of white workers in both the overall sample and the two educational group subsamples. If employers know the significant productivity differences between black and white workers, they have strong incentives to statistically discriminate on the basis of

[14] In Altonji and Pierret (2001), actual experience is defined as the total number of weeks in which the respondent worked after they leave school for the first time. Our actual experience measure is more compatible with the tenure measure.

[15] We use the 2006 released AFQT-3 as our measure of AFQT. Within each three-month age group each individual is given a percentile score that ranges between 0 and 100. NLS staff recommend using the AFQT-3 because it is renormed controlling for age.

[16] We also calculate the annual wage growth rate for four groups of interest, white high school graduates, black high school graduates, white college graduates, and black college graduates. The group of white college graduates has the highest annual wage growth rate while the growth rate only vary slightly across the other three groups.

race. In the next section, we will carry out empirical analysis to examine racial statistical discrimination in detail.

Table 2.1: Summary Statistics

	Total		High School		College	
	Whites	Blacks	Whites	Blacks	Whites	Blacks
Real Hourly Wage	1294.36	1019.17	1086.32	890.73	1807.81	1656.39
	(820.58)	(619.03)	(529.46)	(461.71)	(1107.63)	(902.90)
Potential Experience	132.29	146.35	135.88	150.26	122.25	132.21
	(85.03)	(86.21)	(86.61)	(87.08)	(79.37)	(80.13)
Actual Experience	111.29	111.84	113.87	113.05	107.43	112.50
	(76.49)	(73.53)	(78.58)	(74.46)	(72.18)	(71.12)
Job Tenure	47.09	41.06	47.77	40.34	49.83	47.11
	(48.59)	(43.58)	(49.72)	(43.23)	(48.89)	(48.31)
Education	13.35	12.70	12.00	12.00	16.74	16.60
	(2.39)	(2.01)	(0.00)	(0.00)	(1.19)	(1.06)
Standardized AFQT	0.502	-0.568	0.167	-0.805	1.344	0.486
	(0.957)	(0.798)	(0.812)	(0.573)	(0.569)	(0.894)
No.Indiviudals	2593	1136	1267	652	688	147
No.Observations	225708	94416	104712	49392	59316	12300

Notes: The data are from the 1979-2008 waves of NLSY79. Standard deviations are in parentheses. Real hourly wages are in cents. Potential experience, actual experience and job tenure are in months.

2.3.2 Empirical Specification

This section describes how we empirically test the predictions of the employer learning and statistical discrimination model developed in this chapter. The learning parameter θ_t implies that the effects of AFQT score and black indicator *Black* vary nonlinearly with time. To simplify the matter, however, we assume a linear relationship between log wage, AFQT score and black indicator in the empirical analysis. To test our predictions, we apply the empirical framework proposed by Farber and Gibbons (1996) and Altonji and Pierret (2001). The wage equation regresses log wages on AFQT score, a black indicator variable that takes 1 if the worker is black and 0 otherwise, education, time interaction terms, and demographic variables:

$$\begin{aligned}\ln w_{i,t} =&\beta_0 + \beta_{AFQT}AFQT_i + \beta_{AFQT,t}(AFQT_i \times t_{i,t}) + \beta_{Black}Black_i \\ &+ \beta_{Black,t}(Black_i \times t_{i,t}) + \beta_S S_i + \beta_{S,t}(S_i \times t_{i,t}) + \beta_\Omega \Omega_{i,t} + \epsilon_{i,t}\end{aligned} \tag{2.26}$$

where $w_{i,t}$ denotes wage, $AFQT$ denotes AFQT score, $Black$ is an indicator variable, S is the education variable, and Ω is a vector of demographic variables and other controls. All time interaction terms are divided by 120, so the coefficient on interaction terms measures the change in wage during a ten-year period. Our main coefficients of interest are the coefficients on $AFQT$ and $Black$, β_{AFQT} and β_{Black}, and the coefficients on $AFQT$ interacted with time t, $\beta_{AFQT,t}$, and $Black$ interacted with time t, $\beta_{Black,t}$.

If employer learning is symmetric, the learning process occurs over the general experience regardless of workers' job turnover rate. In contrast, asymmetric learning indicates that only current firms learn about workers' productivity over time, implying a continuous learning process over tenure but not over general experience. To distinguish between symmetric and asymmetric learning, actual experience X and tenure T are used as time measure t in equation (2.26), respectively, and the corresponding estimating equations are as follows:

$$\begin{aligned}\ln w_{i,t} =& \beta_0^X + \beta_{AFQT}^X AFQT_i + \beta_{AFQT,X}^X (AFQT_i \times X_{i,t}) + \beta_{Black}^X Black_i \\ &+ \beta_{Black,X}^X (Black_i \times X_{i,t}) + \beta_S^X S_i + \beta_{S,X}^X (S_i \times X_{i,t}) + \beta_\Omega^X \Omega_{i,t} + \epsilon_{i,t}^X \end{aligned} \tag{2.27}$$

$$\begin{aligned}\ln w_{i,t} =& \beta_0^T + \beta_{AFQT}^T AFQT_i + \beta_{AFQT,T}^T (AFQT_i \times T_{i,t}) + \beta_{Black}^T Black_i \\ &+ \beta_{Black,T}^T (Black_i \times T_{i,t}) + \beta_S^T S_i + \beta_{S,T}^T (S_i \times T_{i,t}) + \beta_\Omega^T \Omega_{i,t} + \epsilon_{i,t}^T. \end{aligned} \tag{2.28}$$

If employer learning is symmetric, both current firms and outside firms learn about workers' productivity. Firms could learn the productivity of a new worker through their past experience, so β_{AFQT}^T is larger than β_{AFQT}^X. The impacts of AFQT score and black indicator on log wages are assumed to vary linearly with the time measure, so $\beta_{AFQT,t}$ and $\beta_{Black,t}$ do not vary whether experience or tenure measure is used. The effect of AFQT score on log wage increases over time, so $\beta_{AFQT,t}$ is positive. If there is no statistical discrimination by race, β_{Black}^X is zero, but β_{Black}^T is very likely to be negative. $\beta_{Black,X}^X$ and $\beta_{Black,T}^T$ are equally negative, implying a widening racial wage gap. On the contrary, racial statistical discrimination predicts that β_{Black}^X should be at least as negative as β_{Black}^T, and equally positive $\beta_{Black,X}^X$ and $\beta_{Black,T}^T$ reflects a narrowing racial wage gap.

On the other hand, the initial coefficients on $AFQT$ and $Black$ are the same whether we use the experience or tenure measure under the assumption of asymmetric learning. The reason is that a worker without any experience must have zero unit of tenure. What is more, the speed of employer learning is faster over tenure than over experience because the employer learning process occurs only over tenure. As a result, tenure interaction terms are larger in magnitude than experience interaction terms.

Depending on the nature of employer learning and the existence of racial statistical discrimination, there are four possible scenarios, and Table 2.2 summarizes the distinct predictions under each scenario. In the empirical analysis, we rely on these predictions to distinguish between two types of employer learning and to explore if statistical discrimination is an important source of racial wage gaps.

Table 2.2: Employer Learning and Statistical Discrimination

	No Racial Statistical Discrimination	Racial Statistical Discrimination
Symmetric Learning	$0 = \beta^X_{AFQT} \leq \beta^T_{AFQT}$	
	$0 < \beta^X_{AFQT,X} = \beta^T_{AFQT,T}$	
	$0 = \beta^X_{Black} \geq \beta^T_{Black}$	$\beta^X_{Black} \leq \beta^T_{Black} < 0$
	$\beta^X_{Black,X} = \beta^T_{Black,T} < 0$	$\beta^X_{Black,X} = \beta^T_{Black,T} > 0$
Asymmetric Learning	$\beta^X_{AFQT} = \beta^T_{AFQT} = 0$	
	$0 \leq \beta^X_{AFQT,X} < \beta^T_{AFQT,T}$	
	$\beta^X_{Black} = \beta^T_{Black} = 0$	$\beta^X_{Black} = \beta^T_{Black} < 0$
	$0 \geq \beta^X_{Black,X} > \beta^T_{Black,T}$	$0 \leq \beta^X_{Black,X} < \beta^T_{Black,T}$

2.4 Empirical Results

In this section, we begin the empirical analysis with the replication of the results reported in Altonji and Pierret (2001) using our sample selection criteria. With potential experience as our time measure, we estimate equation 2.26, and present the results in Table 2.3. The sample in column (1) includes observations coming from interview years 1979-1992, which is the sample used in Altonji and Pierret (2001). Column (2) reports analogous results of our longer sample, the 1979-2008 waves of NLSY79. Because of several differences in sample construction, the results we obtain differ slightly from those presented in Altonji and Pierret (2001). However, their main qualitative results are still presented in Table 2.3.

Altonji and Pierret (2001) find that employers gradually learn about workers' productivity as they accumulate more information, but there is little evidence for statistical discrimination on the basis of race. The results shown in column (1) are supportive for their findings. The

Table 2.3: The Effects of AFQT and Black on Log Wages

Model:	(1)	(2)
Education	0.088***	0.071***
	(0.007)	(0.006)
Education × Experience/120	-0.034***	-0.002
	(0.009)	(0.004)
Standardized AFQT	0.035*	0.058***
	(0.014)	(0.012)
AFQT × Experience/120	0.068***	0.037***
	(0.018)	(0.009)
Black	-0.030	-0.036
	(0.026)	(0.022)
Black × Experience/120	-0.084**	-0.053***
	(0.031)	(0.015)
R^2	0.274	0.346
Sample	Years 1979-1992	Years 1979-2008
No.Observations	177288	317988

Notes: The experience measure is years of potential experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

coefficients of 0.035(0.014) on $AFQT$ and 0.068(0.018) on the AFQT-experience interaction imply that the impact of a one-standard-deviation increase in $AFQT$ will rise from 0.035 when potential experience is 0 to 0.103 when potential experience is 10 years. Employers learn workers' productivity from newly acquired information over time, so the weight they put on hard-to-observe correlates of productivity increases over time. If employers obey the law and do not use race as information, then race works as a hard-to-observe correlate of productivity. The initial coefficient on *Black* is $-0.030(0.026)$ and the coefficient on the interaction term between *Black* and experience is $-0.084(0.031)$, so the racial wage gap is initially not statistically different from zero, but rising sharply with experience. The regression coefficients on *Black* confirm Proposition 1, and indicate that employers do not use racial information to determine wage at the time of initial hire.

We obtain qualitative similar results using the longer sample from interview years 1979-2008. However, $AFQT$ and *Black* now have a flatter profile with experience. Compared with the results in column (1), the coefficients on $AFQT$ and *Black* are greater in magnitude and the coefficients on their interaction terms are much smaller in size, but all statistically significant coefficients in column (1) remain significant. The change in the time paths of $AFQT$ and

Black is possibly driven by the non-linear employer learning process. In our empirical analysis, we assume that the effects of *AFQT* and *Black* on log wages vary linearly with time measure to keep the interpretation of coefficients simple.

2.4.1 The Full Sample

In this section, we use the full sample to test the main predictions of our learning-based statistical discrimination model. Our test strategy has two main focal points. First, we analyze how the racial wage gaps vary over time to examine whether or not employers statistically discriminate against black workers. Second, we compare the differences between coefficients of interests in models using experience and using tenure as time measure to test two learning hypotheses.

There is a large body of empirical research on racial wage gap, especially for male workers. It is widely acknowledged that there is a notable black-white wage gap for male workers. In a recent study, Lang and Manove (2011) argue that the substantial racial wage gaps could not be explained by the differences in the quality of schools attended by blacks and by whites, providing evidence that statistical discrimination is one source of the black-white wage gaps. In that case, our learning-based racial statistical discrimination predicts a narrowing racial wage gap over time because the accumulation of rich information enables employers to base their payments more on true productivity and less on racial information. If racial statistical discrimination is absent in the labor market, then our model indicates that the racial wage gap will widen resulting from the negative correlation between productivity and race. Therefore, we will examine the time path of racial wage gap to test for statistical discrimination on the basis of race.

To distinguish between symmetric and asymmetric learning, experience and tenure are used as time measure in the wage regression, respectively. From this point on, actual experience will be used as our measure of experience since it is a more accurate measure of workers' labor market experience and the constructions of actual experience and tenure are more consistent with each other. Symmetric and asymmetric employer learning have different predictions regarding the initial coefficients on *AFQT* and *Black* as well as the size of the coefficients on the interaction terms between models using experience and tenure as time measure. Different initial coefficients and relatively similar coefficients on the interaction terms are supportive for symmetric learning while asymmetric learning implies similar initial coefficients and different coefficients on variables interacted with time measure.

Table 2.4: The Effects of AFQT and Black on Log Wages in the Full Sample

	Experience	Tenure
Model:	(1)	(2)
Standardized AFQT	0.068***	0.076***
	(0.011)	(0.010)
AFQT × Experience/120	0.034***	
	(0.010)	
AFQT × Tenure/120		0.049**
		(0.017)
Black	-0.025	-0.077***
	(0.020)	(0.017)
Black × Experience/120	-0.048**	
	(0.018)	
Black × Tenure/120		0.024
		(0.033)
R^2	0.371	0.381
No.Observations	317988	317988

Notes: The experience measure is years of actual experience. Specifications (1) and (2) control for education, education interacted with experience or tenure, urban residence, region of residence, a cubic in experience and years effects. Specification (2) also controls for a cubic in tenure. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Specifications (1) and (2) in Table 2.4 estimate the wage equation for the full sample. The coefficients on AFQT-experience and AFQT-tenure interaction terms, 0.034(0.010) and 0.049(0.017), are both positive and significant, so we confirm the findings reported in previous studies, that is, employer learning does occur in the labor market. As workers gain more experience, employers learn about their productivity over time, so the weight on correlate of productivity, $AFQT$, rises over time. The coefficient on $AFQT$ is large in both specifications, implying that employers might directly observe parts of workers' productivity at the time of initial hire and learn more as additional information become available over time.[17]

As shown in column (1), the coefficient of $-0.025(0.020)$ on *Black* is insignificantly negative, and the coefficient of $-0.048(0.018)$ on *Black* interacted with experience is a significant negative number. The fact that the racial wage gap is initially very small but increasing sharply with experience is in line with the model of no statistical discrimination by race. A similar

[17] The assumption of linear relationship between log wage and correlates of productivity may also contribute to the positive and sizable initial coefficients.

finding is reported in Altonji and Pierret (2001) and Mansour (2012).[18] The results using tenure as time measure are presented in column (2). At the time of initial entry into the labor market, black workers earn wages that about 7.7 percent lower than those received by their white counterparts with the same AFQT score, and the wage gap decreases insignificantly with workers' tenure, providing some evidence for racial statistical discrimination. Therefore, the use of different time measures in wage regression gives conflicting results, and we can not draw any definite conclusion regarding the issue of racial statistical discrimination.

To differentiate between two types of employer learning, we need to compare the main coefficients of interest in column (1) and column (2). We test whether or not the coefficients obtained from these two specifications are significantly different from each other. The P-values for the difference between these two sets of coefficients indicate that the coefficients on $AFQT$ are not significantly different from each other ($p = 0.291$), but the coefficient on Black-tenure interaction term differs significantly from that on Black-experience interaction term ($p = 0.017$), providing evidence in favor of asymmetric learning. However, the significantly different coefficients on $Black$ ($p = 0.001$) and qualitatively similar coefficients on $AFQT$ interacted with time measure, experience or tenure ($p = 0.323$), are consistent with the predictions of symmetric learning. Overall, the empirical evidence on whether employer learning is symmetric or asymmetric is inconclusive.[19] It is worth noting that the existing empirical literature offers no conclusive evidence on the nature of employer learning. Schonberg (2007) find that employer learning is mostly symmetric even though there are important differences across educational groups. Pinkston (2009)'s empirical results suggest that asymmetric employer learning plays a role that is at least as much important as symmetric learning during an employment spell.

To summarize, the full sample gives confusing results concerning employer learning and statistical discrimination. The results using experience as time measure imply the absence

[18] Altonji and Pierret (2001) find little evidence for statistical discrimination in wages on the basis of race, and argue that statistical discrimination plays a relatively unimportant role in the racial wage gap. Mansour (2012) confirms Altonji and Pierret (2001)'s finding of no evidence for racial statistical discrimination, but his empirical results imply that the pattern might differ across occupations. Both studies examine racial statistical discrimination under the assumption of symmetric employer learning.

[19] As a robustness check, we also include both experience and tenure interaction terms in the regression models, and compare the coefficients on experience and tenure interaction terms. The regression results are similar, the coefficients on $AFQT$-experience interaction terms are qualitative similar ($p = 0.772$) and the coefficients on Black-experience interaction terms are significantly different ($p = 0.008$). Again, the coefficients on $AFQT$ and Black interaction terms provide mixed evidence regarding the nature of employer learning. The regression results are shown in column (1) of Table 2.10.

of racial statistical discrimination in the labor market but the use of tenure measure leads to an opposite conclusion. The comparison between the empirical results using different time measures also provides mixed evidence for the nature of employer learning.

2.4.2 High School Graduates and College Graduates

An important finding in the employer learning literature is that the employer learning process varies across different educational groups. Arcidiacono, Bayer, and Hizmo (2010) propose that employers gradually learn about the productivity of high school graduates, but for college graduates, employers nearly perfectly observe their productivity at the time of hire. They conclude that a college degree helps workers directly reveal key aspects of their productivity, and thus employer learning is more important for high school graduates. Schonberg (2007) also finds that there are important differences across educational groups with respect to the process of employer learning. When workers involved are college graduates, the empirical evidence is potentially consistent with asymmetric learning model.

In this section, we focus our attention on two educational groups of interest, high school graduates and college graduates, and perform the empirical analysis for these two subsamples. We estimate the wage equations 2.27 and 2.28 on these two educational groups, respectively, and omit the education variable and its interaction terms from the regressions since the education level does not vary much within each group.

Table 2.5 presents the estimating results for high school graduates and college graduates. Specifications (1) and (2) in Table 2.5 estimate the wage regression for the high school sample where experience and tenure are used as the time measure, respectively. The coefficients on AFQT interaction terms are positive and statistically significant, 0.035(0.011) and 0.075(0.023), suggesting that employers gradually learn about the productivity of high school graduates. The significantly negative coefficient on Black in both specifications (1) and (2), −0.057(0.027) and −0.099(0.024), provides empirical evidence for racial statistical discrimination against high school graduates. Employers know the average productivity of black workers is lower than that of white workers, and use race as information to determinate wage of newly hired workers. They pay black workers less than apparently similar white workers because black workers are associated with lower average productivity. The coefficient of −0.023(0.022) on Black interacted with experience and the coefficient of 0.059(0.047) on Black interacted with tenure suggest that the racial wage gap does not change much over

Table 2.5: The Effects of AFQT and Black on Log Wages in Two Education Samples

	High School Grad		College Grad	
Model:	(1)	(2)	(3)	(4)
Standardized AFQT	0.060***	0.062***	0.128***	0.171***
	(0.014)	(0.013)	(0.025)	(0.023)
AFQT × Experience/120	0.035**		0.045	
	(0.011)		(0.023)	
AFQT × Tenure/120		0.075**		-0.022
		(0.023)		(0.040)
Black	-0.057*	-0.099***	0.136**	0.113*
	(0.027)	(0.024)	(0.047)	(0.046)
Black × Experience/120	-0.023		-0.085*	
	(0.022)		(0.038)	
Black × Tenure/120		0.059		-0.141
		(0.047)		(0.076)
R^2	0.219	0.235	0.264	0.274
No.Observations	153456	153456	70848	70848

Notes: The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. Specifications (2) and (4) also control for a cubic in tenure. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

experience but decreases insignificantly over tenure. Consistent with the predictions of racial statistical discrimination, employers reduce their reliance on racial information as additional information about workers' productivity become available, so the racial wage gap declines over time.

If employer learning is asymmetric, the use of different time measures, experience or tenure, in the wage regression will yield qualitatively similar coefficients on $AFQT$ and $Black$, but significantly different coefficients on these variables interacted with time measure. The coefficients on $AFQT$ are quite similar, 0.060(0.014) using experience and 0.062(0.013) using tenure, and a P-value of 0.831 fails to reject the null hypothesis that these two coefficients are equal. In contrast, the coefficient on AFQT interacted with experience, 0.035(0.011), is much smaller that on AFQT interacted with tenure, 0.075(0.023), and these two coefficients are significantly different from each other.[20] The quantitatively similar coefficients on $AFQT$ and significantly different coefficients on its interaction terms indicate that employer learning

[20]When we include both experience and tenure interaction terms in Table 2.10, however, we fail to reject that the coefficient on $AFQT$ interacted with experience is significantly different from that on $AFQT$ interacted with tenure ($p = 0.209$) for high school graduates.

is more likely to be asymmetric. As discussed earlier, the coefficients on *Black* using either experience or tenure are significantly negative, $-0.057(0.027)$ and $-0.099(0.024)$. However, the equality of these two coefficients are rejected at the significant level of 5%, conflicting the predictions of asymmetric learning. The comparison between the coefficient on Black interacted with experience and that on Black interacted with tenure provides further empirical evidence supporting asymmetric learning.[21] The racial wage gap only slightly changes with experience but decreases greatly over tenure, and these two coefficients significantly different from each other.

Overall, the results for high school graduates presented in column (1) and (2) of Table 2.5 are generally supportive for asymmetric learning and statistical discrimination by race. The only exception is that the equality of coefficients on *Black* using different time measures are rejected by the test even though both coefficients have the predicted negative sign. One possible explanation is that employers statistically discriminate against black workers more on jobs require prior experience than on entry-level jobs.

Columns (3) and (4) of Table 2.5 show the regression results for college graduates. In each specification, the coefficient on *AFQT* is large and statistically significant but the coefficient on AFQT interacted with time measure is insignificant and relatively small. The time trend of the *AFQT* coefficient provides little evidence for employer learning, therefore, employers have nearly perfect information about the productivity of newly hired college graduates. In contrast to high school graduates, college-educated black workers earn a higher wage that their white counterparts when they first enter the labor market or make a job change, and this black wage premium declines over time. This initial wage premium for black college graduates is also reported in Arcidiacono, Bayer, and Hizmo (2010). The existence of a substantial black wage premium for college graduates actually is a robust feature of the U.S. labor market.

The results for college graduates shown in Table 2.5 confirm Arcidiacono, Bayer, and Hizmo (2010)'s finding that key aspects of productivity are directly revealed upon initial entry into the college market. Employers almost perfectly observe the productivity of college graduates at the time of initial hire, and learn very little additional productivity over time. They explain that information contained on the resumes of college graduates, such as grades, majors and the college attended, help college-educated workers directly reveal their productivity.

[21] Consistent with our findings reported here, the coefficients on Black interacted with time measure are significantly different from each other($p = 0.079$) in the pooled sample as shown in column (2) of Table 2.10.

Therefore, the learning-based racial statistical discrimination model developed in this chapter is not applicable to the group of college graduates.

A related finding from the empirical research on racial wage gap is that black-white wage gap is smaller or even non-exist for high-skilled workers. Neal and Johnson (1996) claims that the racial wage gap for male declines with the skill level, and a similar finding is also reported in Lang and Manove (2011), black and white men have similar earnings at high levels of education and AFQT score. Our learning-based racial statistical discrimination model provides a plausible explanation for the lack of racial wage gap among high-skilled workers. In high-skill labor market primarily dominated by a better-educated workforce, employers have less incentives to statistically discriminate against black workers because they could accurately assess workers' productivity.

The results for the full sample shown in Table 2.4 are the mixed results of different educational groups. The reason why we are unable to obtain clear-cut results for the full sample is that the employer learning process varies across different education groups. We focus on high school graduates and college graduates in our empirical analysis since the sample sizes for high school and college drop-outs are small and their results are much less statistically significant.[22]

2.5 Robustness Checks

2.5.1 Pure or Imperfect Asymmetric Learning

Our learning-based racial statistical discrimination model assumes that learning is either purely symmetric or purely asymmetric. Pure symmetric learning means that current and outside firms have the same information about workers' productivity. Pure asymmetric learning, in contrast, suggests that only current firms accumulate information about workers' productivity and outside firms receive no new information.

It is likely that outside firms receive some new information about workers' productivity but

[22]In the empirical analysis, we use data from longitudinal surveys, so our data set is repeated cross-sections over time. In other words, we observe the same individual in more than one condition. Therefore, we apply the White-Huber standard errors to account for multiple observations per individual. As a robustness check, we randomly select one observation for each individual to form a random cross-sectional sample of my data, and repeat our analysis for this sample. The regression results are shown in Table 2.11 and 2.12.

current firms have superior information than outside firms do, then employer learning is termed as imperfectly asymmetric. In the case of imperfect asymmetric learning, outside firms could learn some aspects of workers' productivity, so employer learning occurs both over experience and over tenure. Schonberg (2007) analyses how impacts of ability and education vary with experience and tenure to distinguish between pure symmetric and imperfect asymmetric learning. If learning is purely symmetric, then the coefficients on education interacted with tenure and AFQT interacted with tenure should both be zero since these variables interacted with experience are included in the regression model. In contrast, non-zero coefficients on tenure interaction terms are consistent with imperfect asymmetric learning, suggesting that both current and outside firms have access to information on workers' productivity but current firms have information advantage over outside firms. Her empirical results using the same NLSY79 data provide evidence for imperfect asymmetric learning among college graduates.[23]

We apply a methodology similar to Schonberg (2007)'s to examine the possibility that employer learning is imperfectly asymmetric instead of purely asymmetric. Our empirical results imply that employer learning process mainly occurs in the high school market, so we only focus on high school graduates here. If some new productivity information is revealed to outside firms, then the learning process takes place not only over tenure but also over general experience, suggesting that employer learning is imperfectly asymmetric. On the other hand, if outside firms are completely excluded from the employer learning process, then employer learning is purely asymmetric and we should only observe learning over tenure. We include both experience and tenure interactions in the regression model and our estimating equation is given by

$$\begin{aligned} \ln w_{i,t} = &\beta_0 + \beta_1 AFQT_i + \beta_2(AFQT_i \times T_{i,t}) + \beta_3(AFQT_i \times X_{i,t}) \\ &+ \beta_4 Black_i + \beta_5(Black_i \times T_{i,t}) + \beta_6(Black_i \times X_{i,t}) \\ &+ \beta_7 \Omega_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{2.29}$$

The main coefficients of interest are β_3, the coefficient on AFQT-experience interaction term, and β_6, the coefficient on Black-experience interaction term. Pure asymmetric learning predicts that both β_3 and β_6 are equal to zero while imperfect asymmetric learning indicates non-zero coefficients on experience interaction terms.

[23] Schonberg (2007) uses the 1979-2001 waves of NLSY79 and restricts the empirical analysis to white males only.

Table 2.6: Pure or Imperfect Asymmetric Learning

Model:	(1)	(2)
Standardized AFQT	0.062***	0.053***
	(0.013)	(0.014)
AFQT × Tenure/120	0.075**	0.062*
	(0.023)	(0.028)
AFQT × Experience/120		0.015
		(0.014)
Black	-0.099***	-0.073**
	(0.024)	(0.027)
Black × Tenure/120	0.059	0.090
	(0.047)	(0.056)
Black × Experience/120		-0.039
		(0.026)
R^2	0.235	0.236
No.Observations	153456	153456

Notes: The experience measure is years of actual experience. Specifications (1) and (2) control for urban residence, region of residence, a cubic in experience, a cubic in tenure, and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The estimating results under the assumption of pure asymmetric learning presented in column (2) of Table 2.5 appear again in column (1) of Table 2.6, for the sake of comparison, and column (2) shows the empirical results applying regression equation 2.29 where both tenure and experience interactions are considered. The fact that the coefficients on AFQT-experience and black-experience interaction terms are not statistically different from zero provides empirical evidence in favor of pure asymmetric learning. Unlike experience interactions, the coefficients on tenure interactions are large in magnitude and statistically significant.[24] To further distinguish between pure and imperfect asymmetric learning, we test whether or not the common regression coefficients presented in specification (1) and (2) are significantly different from each other. The P-values suggest that there are no statistical differences between these two sets of coefficients, therefore, employer learning is more likely to be purely asymmetric. The empirical results presented in Table 2.6 indicate that outside firms seem not to have access to new information about workers' productivity accumulated over time, implying that, for high school graduates, employer learning tends to be more

[24]The coefficient of 0.090(0.056) on black interacted with tenure is slightly significant at the 10% significant level.

supportive of purely asymmetric rather than imperfectly asymmetric.

2.5.2 Match Quality and Job Mobility

In order to concentrate on employer learning and statistical discrimination, the theoretical model developed in this chapter does not consider the quality of firm-worker match. If various racial groups are associated with different job mobility patterns, match quality might vary between black and white workers.

Our empirical results support the view that, in the high school market, employers use race as a source of information to infer workers' productivity and thus statistically discriminate against black workers. Whenever black high school graduates start a new job, employers pay them significantly less than their white counterparts conditional on the AFQT score. One possible explanation for the racial wage gap is that black high school graduates on average have a worse firm-worker match quality than do white high school graduates. If the racial wage gap reflects racial differences in match quality rather than statistical discrimination, we could expect that black high school graduates generally switch firms more frequently than do white high school graduates. Poorly matched black workers are more likely to move between firms voluntarily or involuntarily.

We test this alternative explanation by estimating a probit model that examines the effect of black indicator on workers' probability of job change. We apply the following estimating equation to high school graduates and college graduates separately:

$$Pr(JobChange_{i,t} = 1) = \Phi(\beta_0 + \beta_1 Black_i + \beta_2 AFQT_i + \beta_3 X_{i,t} + \beta_4 \Omega_{i,t}), \tag{2.30}$$

where the main coefficient of interest is β_1. If the racial wage gap in the high school market could be attributed to match quality differences across racial groups instead of racial statistical discrimination resulting from employer learning, we could expect a positive β_1 in the high school sample. That is, black high school graduates change job more frequently than their white counterparts.

The results of the probit regression are presented in Table 2.7. As shown in column (1), the probability of job change is 3.6% lower for black high school graduates, and the marginal effect of black indicator is statistically significant at the 5% significant level. The fact that black workers are less likely to change job rules out the alternative interpretation that the

Table 2.7: The Impact of Black Indicator on Job Change Probability

Model:	(1)	(2)
Black	-0.036*	0.025
	(0.015)	(0.036)
Standardized AFQT	-0.022*	-0.074***
	(0.008)	(0.018)
Sample	High School	College
No.Observations	466704	181452

Notes: The dependent variable is a dummy variable for job change. Specifications (1) and (2) control for actual experience, urban residence, region of residence and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

racial wage gap in the high school market reflects racial differences in firm-worker match quality. The results for college graduates appear in column (2). It turns out that, for college graduates, there is no statistical racial difference in the job change probability. The probit regression results shown in Table 2.7 provide further empirical evidence for the learning-based racial statistical discrimination model established in this chapter. In the high school market, black workers face statistical discrimination at the time of initial hire, therefore, black workers tend to change job less frequently than do white workers to mitigate the effects of discrimination. In the college market, employers could directly observe key aspects of workers' productivity and learn very little additional information over time. As a result, employers have less incentives to discriminate against black workers, and the job change rate does not vary between black and white college graduates.

The results shown in Table 2.7 also indicates that workers of high productivity might have better match quality than low-ability workers. A one standard deviation increase in the AFQT score reduces the job change rate of high school graduates and college graduates by 2.2% and 7.4%, respectively. The positive association between productivity and match quality is stronger in the college market than in the high school market. The negative marginal effect of the AFQT score on the probability of job change obtained from the high school graduates sample is also consistent with one well-known consequence of asymmetric learning, the adverse selection of job movers. The productivity of workers who switch firms is lower than that of workers who stay with their employers.[25]

[25]Gibbons and Katz (1991) argue that laid-off workers are generally less able than exogenous movers. Their empirical results that the wage loss for laid-off workers is greater than that for exogenous movers

In short, the results of the probit model provide several pieces of evidence in favor of our main findings. First, the fact that black high school graduates change job less frequently than do white high school graduates strengthens our previous finding that black workers are statistically discriminated in the high school market. Furthermore, there is no statistical racial difference in job mobility patterns in the college market, confirming that employers almost perfectly observe the productivity of college-educated workers and therefore have weak incentives to discriminate against blacks. Second, the negative and statistically significant marginal effect of AFQT score on job change rate are consistent with our finding that employer learning is asymmetric in the high school market.

2.5.3 Occupation and Industry

Black and white workers are likely to associated with jobs of different skill levels. If that is the case, there may be explanations other than learning-based racial statistical discrimination for our findings for high school graduates. One possible alternative explanation is that black workers are more likely to be hired into low-skill-level jobs at the start of their career and to be trapped for a while in such jobs. The initial job assignments could influence the entire menu of career paths. What appears to be evidence of racial statistical discrimination might could be attributed to differences in the skill level of jobs taken by black and white workers.

To test the possibility that racial wage gap is driven by blacks and whites being sorted into jobs of different skill levels, we add the initial occupation variable to the estimating equation as an additional control, and repeat the empirical analysis separately for high school graduates and college graduates.[26] The regression results are presented in Table 2.8.

We obtain qualitatively similar results with the inclusion of initial occupation,[27] so our main findings still hold. Occupation sorting could not explain the results that we attribute to learning-based racial statistical discrimination. In the high school market, the *Black* coefficient is initially negative and significant, and rises insignificantly with tenure, providing

support this view. In this chapter, however, we do not distinguish between involuntary and voluntary job movers due to data limitations.

[26]We distinguish 7 occupations: professional workers; managers; sales workers; clerical workers; craftsman and operatives; agricultural labors; and service workers.

[27]Mansour (2012) finds that there is substantial variation in the time path of black coefficients across occupations. The results shown in Table 2.8 indicate that the inclusion of initial occupation does affect the coefficients on *Black* and black interacted with time measure. Therefore, the extent of statistical discrimination by race may vary across occupations.

Table 2.8: The Effects of Black on Log Wages Controlling for Initial Occupation

	High School		College	
Model:	(1)	(2)	(3)	(4)
Black	-0.084**	-0.122***	0.130**	0.117*
	(0.032)	(0.028)	(0.048)	(0.047)
Black × Experience/120	-0.014		-0.103**	
	(0.023)		(0.039)	
Black × Tenure/120		0.067		-0.206**
		(0.049)		(0.075)
R^2	0.242	0.255	0.316	0.324
No.Observations	119496	119496	65376	65376

Notes: The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience, years effects and initial occupation. Specifications (2) and (4) also control for a cubic in tenure. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

evidence that our main results can not be attributed to differences in the skill level of jobs taken by different racial groups. Employers initially statistically discriminate against black high school graduates but learn about their productivity gradually as more information become available, so the racial wage gaps shrink over time. Including the initial occupation in the regression also does not alter the results for college graduates. College-educated blacks do not face statistical discrimination on the basis of race, instead, they earn an initial black wage premium conditional on productivity.

We further explore the role of job assignment by examining the effect of initial industry on the observed racial wage gap.[28] With initial industry added, we redo the empirical analysis for two educational groups of interest. The results shown in Table 2.9 closely resemble those of Table 2.8. Therefore, the racial wage gap can not be explained by the possible variation in industry that members from different racial groups work in.[29]

[28]We distinguish 12 industries: agriculture; mining; construction; manufacturing; transportation, communication, and utilities; wholesale and retail trade; finance, insurance, and real estate; business and repair services; personnel services; entertainment and recreation services; professional and related services; and public administration.

[29]We also experiment by controlling for initial occupation and industry simultaneously, the main results are not affected. The empirical results are available upon request.

Table 2.9: The Effects of Black on Log Wages Controlling for Initial Industry

	High School		College	
Model:	(1)	(2)	(3)	(4)
Black	-0.096**	-0.136***	0.122**	0.114*
	(0.030)	(0.028)	(0.047)	(0.046)
Black × Experience/120	-0.017		-0.089*	
	(0.023)		(0.040)	
Black × Tenure/120		0.066		-0.185*
		(0.051)		(0.075)
R^2	0.251	0.263	0.312	0.318
No.Observations	119124	119124	65580	65580

Notes: The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience, years effects and initial industry. Specifications (2) and (4) also control for a cubic in tenure. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.6 Conclusion

In this chapter, we combine elements of both employer learning and statistical discrimination theories to develop a learning-based racial statistical discrimination model. We formulate a framework that nests both symmetric and asymmetric employer learning, and examine whether employers statistically discriminate against black workers under each scenario.

Our estimating results show that high school graduates and college graduates are associated with different patterns of employer learning. At the time of initial hire, employers have to rely on some easily observable characteristics to estimate the productivity of high school graduates, and they gradually update their expectations and base their payment more on true productivity as they acquire more information. For college graduates, employers are able to learn most of their productivity upon initial entry into the labor market, and very little learning occurs after hire. As a result, we mainly focus our attention on high school graduates. The time paths of racial wage gap in the high school market indicate that employers use race as information to infer workers' productivity and black workers are statistically discriminated. By comparing the coefficients of interests from wage regressions using either general experience or job tenure as time measure, we find empirical evidence for asymmetric learning in the high school market. As high school graduates spend more time in the labor market, their current firms accumulate more information and gradually learn about their productivity, but outside firms are insulated from the learning process and are unable to update their expectations about workers' productivity.

In this chapter, we simply assume that the effects of AFQT score and racial variable on log wage vary linearly with time when performing the empirical analysis. However, some empirical studies indicate a varying speed of employer learning. Lange (2007) constructs a framework to formally estimate the speed of employer learning and shows that employers actually learn very fast in the first few years.[30] One direction for future research is to precisely estimate the speed of employer learning and to test one important implication of our model, that is, employers learn faster over tenure than over experience in the case of asymmetric learning. The speed of employer learning is also crucial for the economic significance of statistical discrimination on the basis of race. The faster the employers learn, the shorter the time period during which employers need to rely on race to predict a worker's productivity.

Most statistical discrimination models build around the assumption that the signal of productivity employers receive from black workers is less reliable than that from white workers at the time of initial hire. Pinkston (2006) applies the framework of employer learning to test this hypothesis, and his estimation results provide evidence supporting this view. Our learning-based racial statistical discrimination model assumes that the signals sent by workers from different racial groups are equally informative. Statistical discrimination arises because employers know the average productivity of black workers is lower than that of white workers. An interesting topic for future research is to relax the assumption of equally informative signals from different racial groups and to investigate its effect on employer learning and racial statistical discrimination.

[30]Lange (2007) shows that the initial expectation errors decline by 50% within 3 years.

2.7 Appendix A

Table 2.10: The Effects of AFQT and Black on Log Wages in the Pooled Sample

	The Full Sample	High School Grad
Model:	(1)	(2)
Standardized AFQT	0.063***	0.053***
	(0.011)	(0.014)
AFQT × Experience/120	0.023	0.015
	(0.012)	(0.014)
AFQT × Tenure/120	0.031	0.062*
	(0.021)	(0.028)
Black	-0.036	-0.073**
	(0.019)	(0.027)
Black × Experience/120	-0.066**	-0.039
	(0.021)	(0.026)
Black × Tenure/120	0.079*	0.090
	(0.040)	(0.056)
R^2	0.384	0.236
No.Observations	317988	153456

Notes: The experience measure is years of actual experience. Specifications (1) controls for education, education interacted with experience and tenure. Both specifications control for urban residence, region of residence, a cubic in experience and tenure, and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.11: The Effects of AFQT and Black in the Cross-sectional Full Sample

	Experience	Tenure
Model:	(1)	(2)
Standardized AFQT	0.056***	0.061***
	(0.016)	(0.013)
AFQT × Experience/120	0.052**	
	(0.017)	
AFQT × Tenure/120		0.107***
		(0.031)
Black	-0.074*	-0.111***
	(0.029)	(0.023)
Black × Experience/120	-0.030	
	(0.030)	
Black × Tenure/120		0.067
		(0.059)
R^2	0.355	0.368
No.Observations	3703	3703

Notes: The experience measure is years of actual experience. Specifications (1) and (2) control for education, education interacted with experience or tenure, urban residence, region of residence, a cubic in experience and years effects. Specification (2) also controls for a cubic in tenure. The numbers in parentheses are standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.12: The Effects of AFQT and Black in the Cross-sectional Sample of High School Graduates

	High School Grad	
Model:	(1)	(2)
Standardized AFQT	0.051*	0.045**
	(0.021)	(0.017)
AFQT × Experience/120	0.043	
	(0.022)	
AFQT × Tenure/120		0.132**
		(0.040)
Black	-0.107**	-0.110***
	(0.039)	(0.032)
Black × Experience/120	-0.008	
	(0.040)	
Black × Tenure/120		0.016
		(0.079)
R^2	0.182	0.206
No.Observations	1733	1733

Notes: The experience measure is years of actual experience. Both specifications control for urban residence, region of residence, a cubic in experience and years effects. Specifications (2) also control for a cubic in tenure. The numbers in parentheses are standard errors.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 3

Employer Learning and Statistical Discrimination Over Time and Across Employers

(ABSTRACT)

This chapter tests the hypothesis of employer learning and statistical discrimination with both the NLSY79 and NLSY97 data, and takes a further look at the employer learning and statistical discrimination process of black high school graduates in the NLSY97. The comparison between these two cohorts reveals that employer learning and statistical discrimination has became stronger over the past decades. We also investigate the effects of various employer-specific characteristics, and identify three influencing factors of employer learning and statistical discrimination, the supervisor-worker race match, supervisor's age, and firm size. Black high school graduates face weaker employer learning and statistical discrimination if they choose to work for a black supervisor, work for an old supervisor, or work in a firm of small size.

3.1 Introduction

Discrimination in the workplace can lead to very negative social consequences, and is also against the law in the United States. Governments have introduced all kinds of policies to reduce discrimination in the labor market. However, rational employers may still use some cheap sources of information about productivity such as education and race to statistically discriminate against workers when making wage offers since statistical discrimination is very difficult to detect and measure in the real world. How does statistical discrimination in the U.S. labor market evolve over the past decades? What could labor force participants possibly do to reduce the statistical discrimination against them in an imperfect world where worker's productivity is unobservable and statistical discrimination is undetectable? This chapter applies the framework of employer learning and statistical discrimination and provides some insights into these questions.

Farber and Gibbons (1996) and Altonji and Pierret (2001) develop the benchmark employer learning and statistical discrimination model based on the signaling model of education[1] and statistical theories of discrimination.[2] Their hypothesis is that employers have very limited information about worker's productivity at the time of initial hire, and thus they distinguish among workers on the basis of easily observable variables that are correlated with productivity. After hire, employers observe worker's performance and gradually reduce their reliance on these easy-to-observe characteristics. They develop a framework to empirically test whether employers statistically discriminate on the basis of easily observable variables such as education and race. Altonji and Pierret (2001)'s framework is widely used in subsequent literature, and many of them extend their basic models to further examine employer learning and statistical discrimination.

A lot of studies in the literature of employer learning implicitly assume that the extent of employer learning and statistical discrimination does not vary with different education groups, and hence pool all education levels together in the empirical analysis.[3] Arcidiacono, Bayer, and Hizmo (2010) propose that education plays more than just a signaling role in the wage determination, and split the sample into high school and college graduates when analyzing employer learning and statistical discrimination. Their results suggest that employers learn slowly about the productivity of high school graduates, but almost perfectly learn the productivity of college graduates at time of initial hire. If different education groups are associated with distinct patterns of employer learning, pooling all education level together can lead to very misleading results.

[1]See Spence (1973) and Weiss (1995).

[2]See Aigner and Cain (1977) and Lundberg and Startz (1983).

[3]Examples of papers that pool all education levels include Bauer and Haisken-DeNew (2001), Pinkston (2006), Lange (2007) and Fadlon (2010).

In the context of an employer learning about worker's productivity, race also appears to be a potential source of information. Lang and Lehmann (2012) provides a good summary of existing racial statistical discrimination theories in the labor market. A statistically discriminating employer may use race along with education and other information to infer the productivity of new workers. An important contribution of Altonji and Pierret (2001) is that their model of employer learning and statistical discrimination can be applied to test for statistical discrimination on the basis of race. Race can enter the model either as an easy-to-observe characteristic or a hard-to-observe characteristic depending on whether employers make use of racial information in the determination of wage. If race is negatively correlated with productivity, and employers use race as information to evaluate worker's productivity, the initially negative racial gap will shrink over time as employers gradually learn. However, if employers do not statistically discriminate on the basis of race, race will act as an hard-to-observe characteristic. In this case, the racial wage gap will be relatively small at the time of labor force entry and widen as workers accumulate experience resulting from the negative correlation between productivity and race.

Altonji and Pierret (2001)'s results are consistent with the hypothesis of no or very limited racial statistical discrimination. The issue of statistical discrimination on the basis of race is also addressed in Arcidiacono, Bayer, and Hizmo (2010). They find empirical evidence for racial statistical discrimination in the high school market where the productivity is initially unobservable.[4] Similarly, Mansour (2012) reports that employers statistically discriminate on the basis of race in occupations with high learning patterns. Using the NLSY79 data, our earlier research also find empirical evidence supporting racial statistical discrimination in the high school market.

The majority of empirical studies on employer learning focus on the NLSY79 sample because of the wealth of information available in this survey. In this chapter, we are interested in the evolution of employer learning and statistical discrimination over the past decades. Therefore, we test the hypothesis of employer learning and statistical discrimination with both the NLSY79 and the NLSY97 data, and examine whether influential findings reported in the NLSY79 also hold for the young NLSY97 generation. By comparing the results between these two generations, we will gain some insight into how employer learning and statistical

[4] In contrast to standard model of employer learning and statistical discrimination, the racial wage gap in the high school market increases with experience in Arcidiacono, Bayer, and Hizmo (2010). To accommodate the increasing racial wage gap, they develop a model that allows the productivity of AFQT to change with experience.

discrimination evolves over time.

Despite the large number of studies conducted on employer learning, there are few studies examine the extent of employer learning and statistical discrimination across different types of employers. The process of employer learning and statistical discrimination may be influenced by various factors, leading to varying extent of employer learning and statistical discrimination across employers. If this is the case, workers may be able to reduce the employer learning and statistical discrimination against them by choosing to working for a specific type of employer. This chapter contributes to current employer learning literature by identifying factors that have a substantial impact on employer learning and statistical discrimination. We use the NSLY97 to investigate the effects of employer-specific characteristics on the process of employer learning and statistical discrimination. The NLSY97 data contains detailed background information on worker's supervisor such as race, gender and age. Supervisors interact with their workers frequently, and usually play a vital role in the evaluation of worker's productivity. Therefore, the NLSY97 data fits well with this research question.

As a starting point of our analysis, we test the hypothesis of employer learning and statistical discrimination for the overall sample and two education groups respectively. We confirm the existence of employer learning and statistical discrimination in the NLSY97 as in the NLSY79, and find that employers use racial information to statistically discriminate against the NLSY97 generation at the time of labor force entry. The NLSY97 data also confirm Arcidiacono, Bayer, and Hizmo (2010)'s proposition that high school and college graduates are associated with different employer learning processes. Employers gradually learn the productivity of high school graduates, but directly learn most parts of productivity of college graduates. In the high school market, it takes a while for employers to fully learn productivity, so race is also a cheap source of information. Racial statistical discrimination is a serious issue for high school graduates. The comparison between the NLSY79 and the NLSY97 indicates that employer learning and statistical discrimination does not disappear but becomes stronger over time despite the enforcement of all kinds of government policies that aim to reduce discrimination in the labor market.

This chapter further investigates the employer learning and statistical discrimination process, and evaluates how it is affected by potential influencing factors. We focus our attention on black high school graduates because they are one of the most disadvantaged groups in the labor market. Black high school graduates face double statistical discrimination, the combined discrimination based on education and discrimination based on race. At the time of initial hire, rational employers make use of education and race to statistically discriminate against black high school graduates because both race and education are correlates of unobservable productivity. As they accumulate experience, employers learn about their productivity from their job performance, and base the wage decision more on productivity and less on these easy-to-observe characteristics. By exploring the impact of various employer-specific characteristics on the process of employer learning and statistical discrimination, we identify three influential factors, the supervisor-worker race match, supervisor's age, and firm size. Our analysis results suggest that black high school graduates could reduce the employer learning and statistical discrimination against them by working for a black supervisor, working for an old supervisor or working in a small firm. While the supervisor-worker race match has the largest effect on employment outcomes, the influence of supervisor's age and firm size is also not negligible.

The contributions of this chapter are two-fold. First, we test influential empirical findings reported in the employer learning literature with the NLSY97, and provide some insights into the employer learning and statistical discrimination process of a relatively young generation as well as the evolution of employer learning and statistical discrimination over time. Second, this chapter cast some light on important factors that could help reduce employer learning and statistical discrimination against black high school graduates.

The rest of this chapter is organized as follows. Section 2 describes the data and econometric models used for the empirical analysis. Section 3 presents the empirical analysis, and discusses the results. Finally, Section 4 concludes and suggests new avenues for future research.

3.2 Data and Empirical Specification

3.2.1 NLSY Data

In this chapter, we use the 1979-1988 waves of National Longitudinal Survey of Youth 1979 (NLSY79) and the 1997-2008 waves of National Longitudinal Survey of Youth 1997 (NLSY97). The NLSY79 is a nationally representative sample of 12,686 men and women born in the years 1957-64, and the NLSY97 is a nationally representative sample of approximately 9,000 young men and women born in the years 1980-84. The reason we only use the 1979-1988 survey years of the NLSY79 is that we want to restrict the NLSY79 to a similar age group as the NLSY97, making the empirical results comparable between these two samples. The NLSY79 respondents were between 23 and 31 years old in 1988 while the NLSY97 respondents were 23-28 years old in 2008.

Both NLSY79 and NLSY97 contain extensive information about young workers' labor market and educational experiences, which enables researchers to investigate the employment experience of young workers. The NLSY97 is more detailed than the NLSY79 in the sense that it contains information about supervisors' characteristics such as race, gender and age. With this information, we are able to study the impact of supervisor-specific characteristics on employer learning process for the NLSY97 generation. We place greater emphasis on the NLSY97 sample in the empirical analysis because supervisors usually are directly involved in the evaluation of worker's productivity.

Our NLSY79 and NLSY97 samples are constructed based on the selection criteria outlined in Altonji and Pierret (2001) and Arcidiacono, Bayer, and Hizmo (2010). We focus our attention on male workers whose labor force participation rate is relatively high compared to female workers, and restrict the sample to black and white male workers with at least 9 years of education. We consider a respondent to have entered the labor market at the time when he left school for the first time, and only include observations after the respondents have made the transition from school to work. Different from most previous empirical studies in the employer learning literature, both cross-sectional sample and oversample of black respondents are kept in the empirical analysis since the focus of our analysis is black high school graduates.

The weekly work history data that contains the week-by-week employment status of each respondent is transformed into monthly work records since we measure potential experience and actual experience in month. We use unique employer identity number to link all the jobs across different survey years, and create the complete employment history for each respondent in the sample. For respondents who hold multiple jobs at the same time, we assign them a new job number, and use the hourly rate of pay for each job and the hours per week worked for each job to calculate the average wage as the wage for the newly constructed job. The real monthly wage are calculated using the CPI-U deflators from Bureau of Labor Statistics, and the base year is 1990. We only include observations with real wages between $1 and $100 in the empirical analysis.

Actual experience and job tenure are created from the monthly work history data while potential experience is calculated as the sum of months since the respondent first left school. Job tenure is the number of months between the job start date and either the job end date or the interview date. Our measure of actual experience is constructed based on the job tenure variable, and is computed as the sum of job tenure for each job.

Our measure of productivity is Armed Forces Qualification Test (AFQT) score, which is a widely used cognitive ability measure in the literature. AFQT is administered to both the NLSY79 and NLSY97 generations, and AFQT score provides a summary measure for basic literacy and numeric skills. We standardize the AFQT score to have a zero mean and a standard deviation of one for each three-month age cohort to make our regression results comparable to earlier studies in employer learning literature.

We construct the education variable as the highest grade completed at the interview date. Workers are split into different groups according to their educational levels. Two educational groups are of particular importance to us, high school graduates and college graduates. High school graduates are defined as workers who have 12 years of schooling at the time of interview, and college graduates are workers who have completed at least 16 years of schooling.

Table 3.1: NLSY79: Summary Statistics

	Total		High School		College	
	Whites	Blacks	Whites	Blacks	Whites	Blacks
Real Wage	999.04	841.47	941.80	789.09	1306.35	1324.88
	(464.17)	(407.68)	(389.37)	(360.75)	(575.41)	(553.52)
Potential Experience	53.99	56.30	56.48	56.94	41.72	40.76
	(31.70)	(31.64)	(31.99)	(31.26)	(26.88)	(28.23)
Actual Experience	43.86	42.49	45.86	43.08	35.94	33.56
	(27.78)	(26.63)	(28.57)	(26.84)	(23.72)	(22.97)
Job Tenure	26.44	25.01	27.67	26.30	24.71	20.33
	(22.27)	(21.70)	(23.50)	(22.90)	(19.49)	(15.69)
Education	12.75	12.20	12.00	12.00	16.36	16.19
	(2.09)	(1.77)	(0.00)	(0.00)	(0.85)	(0.44)
Standardized AFQT	0.381	-0.673	0.202	-0.799	1.311	0.578
	(0.936)	(0.755)	(0.802)	(0.575)	(0.553)	(0.915)
No.indiviudals	2081	801	1059	441	431	75
No.observations	82596	29112	43344	15960	14760	2316

Notes: The data are from the 1979-1988 waves of the NLSY79. Standard deviations are in parentheses. Real hourly wages are in cents. Potential experience, actual experience and job tenure are in months.

Table 3.1 and 3.2 show the summary statistics for our NLSY79 and NLSY97 samples. We

Table 3.2: NLSY97: Summary Statistics

	Total		High School		College	
	Whites	Blacks	Whites	Blacks	Whites	Blacks
Real Hourly Wage	911.95	786.14	852.86	774.48	1221.79	1065.93
	(550.33)	(520.30)	(428.00)	(541.76)	(660.03)	(649.82)
Potential Experience	56.79	61.56	58.83	57.95	44.96	50.35
	(30.22)	(29.83)	(29.95)	(27.34)	(25.82)	(30.12)
Actual Experience	34.17	34.84	36.62	34.74	26.28	27.68
	(24.02)	(23.12)	(24.50)	(22.97)	(20.41)	(20.37)
Job Tenure	15.31	14.38	16.51	15.41	14.46	12.15
	(16.31)	(15.49)	(17.26)	(16.37)	(13.94)	(12.83)
Education	12.84	12.28	12.00	12.00	16.51	16.48
	(2.29)	(2.08)	(0.00)	(0.00)	(0.83)	(0.87)
Standardized AFQT	0.316	-0.429	0.108	-0.515	1.109	0.252
	(1.013)	(0.719)	(0.901)	(0.611)	(0.910)	(0.926)
No.Indiviudals	1681	685	620	261	437	82
No.Observations	67044	24624	26556	9972	12456	2256

Notes: The data are from the 1997-2008 waves of the NLSY97. Standard deviations are in parentheses. Real hourly wages are in cents. Potential experience, actual experience and job tenure are in months.

are especially interested in the groups of high school graduates and college graduates, so we also present the summary statistics for these two education groups. In the sample of college graduates, the proportion of black workers is relatively small, reflecting the domination of white workers in the college market.

As we can see from Table 3.1 and 3.2, the average lengths of actual experience and job tenure are much shorter in the NLSY97 than in the NLSY79, and the average real hourly wage in the NLSY97 is much lower compared with that in the NLSY79. For example, a black worker on average has 35 months of actual experience and 14 months of tenure, and earns an hourly wage of \$7.86 in the NLSY97, whereas the NLSY79 numbers are 42, 25 and \$8.41, respectively. The differences between these two samples are not surprising due to the slight difference in the age range.

However, AFQT score gap between blacks and whites exists in both samples. In the NLSY79, the average AFQT score of black workers is about one standard deviation lower than that of their white counterparts except for the college graduates whose racial AFQT score difference is around 0.7 standard deviation. For the NLSY97 sample, the white-black AFQT score gap is slightly smaller for the overall sample and the group of high school graduates. The racial difference in AFQT score turns out to be a robust feature of the NLSY data. Rational and profit-maximizing employers have strong incentives to statistical discriminate against black workers when the productivity of workers is not directly observable. The issue of statistical discrimination on the basis of race will be addressed in detail in the empirical analysis.

3.2.2 Empirical Specification

Following Farber and Gibbons (1996) and Altonji and Pierret (2001), we formulate a simple econometric model to test the hypothesis of employer learning and statistical discrimination. For the overall sample, we regress the log wages $lnw_{c,i,t}$ on education $S_{c,i}$, AFQT score $AFQT_{c,i}$, black indicator $Black_{c,i}$, and their interaction terms with experience $X_{c,i,t}$ controlling for the demographic information $\Omega_{c,i,t}$. All the time interaction terms are divided by 120 because we want the coefficient on the interaction terms to represent the wage change over a ten-year time period. The log wage equation is as follows:

$$\begin{aligned} \ln w_{c,i,t} =& \beta_0^c + \beta_{AFQT}^c AFQT_{c,i} + \beta_{AFQT,X}^c (AFQT_{c,i} \times X_{c,i,t}) + \beta_{Black}^c Black_{c,i} \\ &+ \beta_{Black,X}^c (Black_{c,i} \times X_{c,i,t}) + \beta_S^c S_{c,i} + \beta_{S,X}^c (S_{c,i} \times X_{c,i,t}) + \beta_\Omega^c \Omega_{c,i,t} + \epsilon_{c,i,t} \end{aligned} \tag{3.1}$$

where c is the cohort index that takes the value 79 or 97, i is the individual index and t is the time index.

To test the employer learning and statistical discrimination hypothesis, we examine how the impacts of education and AFQT score on worker's wage change with experience. If employers statistically discriminate against workers on the basis of education, they will rely heavily on educational information at the time of initial hire, and gradually reduce their reliance on education as workers spend more time in the labor market. On the other hand, the weight employers put on AFQT score, our measure of productivity, is initially small, but increases over time as employers learn about worker's productivity from newly available information. In the econometric model, our main coefficients of interest are the coefficient on AFQT score, β_{AFQT}^c, the coefficient on education, β_S^c, the coefficient on AFQT interacted with experience, $\beta_{AFQT,X}^c$, and the coefficient on education interacted with experience, $\beta_{S,X}^c$. The employer learning and statistical discrimination model predicts a large positive β_S^c and a negative $\beta_{S,X}^c$, reflecting the declining impact of education on the determination of wage. In contrast, AFQT score should play an increasing role in the wage decision, implying a small β_{AFQT}^c and a positive $\beta_{AFQT,X}^c$.

The wage regression model (3.1) could also be applied to address the issue of statistical discrimination on the basis of race. In the model of employer learning and statistical discrimination, race could enter the model either as an easy-to-observe characteristic such as education or as a hard-to-observe characteristic such as AFQT score. If employers make use of racial information in the wage decision, race will act as an easy-to-observe characteristic, and the impact of race on worker's wage will decline over time. We are expected to observe a large negative β^c_{Black} and a positive $\beta^c_{Black,X}$ because black is a negative correlate of productivity. However, if employers obey the law and do not use race to infer worker's productivity, race will behave as a hard-to-observe characteristic in the model of employer learning and statistical discrimination. A small β^c_{Black} and a negative $\beta^c_{Black,X}$ are consistent with the implications of no statistical discrimination on the basis of race.

There is a large body of research analyzing employer learning and statistical discrimination for the NLSY79 sample. In this chapter, we will focus our attention on the NLSY97 sample, and test important findings reported in the literature with this young generation. Furthermore, we are also interested in the evolution of employer learning and statistical discrimination over time. To address this question, we will restrict the NLSY79 to similar age groups as the NLSY97, and compare regression results between these two generations. Significant differences between these two sets of coefficients, $(\beta^{79}_{AFQT}, \beta^{79}_{AFQT,X}, \beta^{79}_{S}, \beta^{79}_{S,X}, \beta^{79}_{Black}, \beta^{79}_{Black,X})$ and $(\beta^{97}_{AFQT}, \beta^{97}_{AFQT,X}, \beta^{97}_{S}, \beta^{97}_{S,X}, \beta^{97}_{Black}, \beta^{97}_{Black,X})$, provide empirical evidence that employer learning and statistical discrimination evolves over time in the U.S. labor market.

Earlier literature reports that different education groups are linked with different patterns of employer learning process. In the empirical analysis, we repeat the regression analysis for two groups of interests, high school graduates and college graduates. The education level does not vary much within each group, so we drop the education variable from the wage regression equation. For each education group, the log wage equation is

$$\begin{aligned} \ln w_{c,i,t} =& \beta^c_0 + \beta^c_{AFQT} AFQT_{c,i} + \beta^c_{AFQT,X}(AFQT_{c,i} \times X_{c,i,t}) + \beta^c_{Black} Black_{c,i} \\ &+ \beta^c_{Black,X}(Black_{c,i} \times X_{c,i,t}) + \beta^c_{\Omega}\Omega_{c,i,t} + \epsilon_{c,i,t}. \end{aligned} \tag{3.2}$$

Arcidiacono, Bayer, and Hizmo (2010) propose that employers gradually learn the productivity of high school graduates but almost perfectly learn key aspects of productivity of college graduates. A college degree helps workers to directly reveal their productivity to the labor market. Using the NLSY79 data, Arcidiacono, Bayer, and Hizmo (2010) find empirical support for their propositions. Our earlier study also confirms these two distinct employer learning processes associated with high school graduates and college graduates in the NLSY79 data. There are no studies in the literature, to the best of my knowledge, that examine the differences in employer learning process across distinct education groups in the NLSY97 data.

If Arcidiacono, Bayer, and Hizmo (2010)'s propositions also hold for the NLSY97 generation, we will observe a steep AFQT-experience profile for the high school graduates, that is, a small β^c_{AFQT} and a large $\beta^c_{AFQT,X}$, and a relatively flat AFQT-experience profile for the college graduates, that is, a large β^c_{AFQT} and a small $\beta^c_{AFQT,X}$. Furthermore, we could test statistical discrimination on the basis of race for each group by examining the time path of the impact of race on log wage. A large negative β^c_{Black} and a positive $\beta^c_{Black,X}$ provide support for racial statistical discrimination while a small negative β^c_{Black} and a negative $\beta^c_{Black,X}$ imply the absence of racial statistical discrimination in the labor market. By comparing the differences between $(\beta^{79}_{AFQT}, \beta^{79}_{AFQT,X}, \beta^{79}_{Black}, \beta^{79}_{Black,X})$ and $(\beta^{97}_{AFQT}, \beta^{97}_{AFQT,X}, \beta^{97}_{Black}, \beta^{97}_{Black,X})$ for each education group, we will gain some understanding of the evolution of employer learning and statistical discrimination for our groups of interest.

In this chapter, we aim to identify factors, such as demographic information of supervisors and firm-specific characteristics, that have some influences on the employer learning and statistical discrimination. To investigate the impact of potential influencing factors, we split the NLSY97 sample into two groups according to factor j, such as supervisor-worker race match, supervisor's age and firm size, estimate the log wage equation (3.3) separately for each group, and compare regression coefficients between these two groups. If factor j does play an important role in employer learning and statistical discrimination, there will be significant differences in these two sets of coefficients. Otherwise, we will obtain qualitative similar results from these two distinct groups, suggesting that the impact of factor j is negligible. Because of the lack of supervisor information in the NLSY79 sample, we focus on the NLSY97 sample and omit the cohort index c in equation (3.3).

$$\begin{aligned} \ln w_{j,i,t} =& \beta^j_0 + \beta^j_{AFQT} AFQT_{j,i} + \beta^j_{AFQT,X}(AFQT_{j,i} \times X_{j,i,t}) + \beta^j_{Black} Black_{j,i} \\ &+ \beta^j_{Black,X}(Black_{j,i} \times X_{j,i,t}) + \beta^j_{\Omega}\Omega_{j,i,t} + \epsilon_{j,i,t}. \end{aligned} \tag{3.3}$$

3.3 Empirical Results

In this section, we first test the hypothesis of employer learning and statistical discrimination with each data set to gain a general understanding of the evolution of employer learning and statistical discrimination over time. More specifically, we apply the regression model (3.1) to the overall sample and the regression model (3.2) to two education groups of particular interest, high school graduates and college graduates, using the NLSY79 and the NLSY97 sample respectively. After that, we focus on the NLSY97 sample to investigate the impact of various demographic variables of supervisors and firm-specific characteristics to identify factors that significantly influence employer learning and statistical discrimination.

3.3.1 Employer Learning and Statistical Discrimination

As a starting point of our empirical analysis, we test Altonji and Pierret (2001)'s employer learning and statistical discrimination hypothesis with the NLSY79 and NLSY97 data. Using the 1979-1992 waves of the NLSY79 data, Altonji and Pierret (2001) find empirical support for statistical discrimination on the basis of education, but little evidence for race-based statistical discrimination. Our analysis results from the 2008 release of the NLSY79 have confirmed Altonji and Pierret (2001)'s findings. We apply the log wage equation (3.1) to each sample, and report the analogous results in Table 3.3. Potential experience and actual experience are used as the experience measure in the wage regression separately. We obtain qualitatively similar results from these two experience measures, so we focus our discussion on actual experience since it is a more accurate measure of worker's labor market experience.

It is clear from column (2) that employer learning and statistical discrimination exists in the short sample of NLSY79. During a ten-year time period, the impact of education drops from 0.077 to 0.054, and the impact of AFQT score increases greatly from 0.037 to 0.099. As new information about productivity show up, education information becomes less important, and employers rely more on productivity in the wage decision.

The results presented in column (4) of Table 3.3 indicate that, for the NLSY97 generation, employers also statistically discriminate on the basis of education. The coefficient on education and education-experience interaction term is 0.068(0.006) and $-0.057(0.015)$, respectively, suggesting that the effect of education on wage is initially large but declines sharply with experience. The impact of our productivity measure, AFQT score, however,

Table 3.3: The Effects of Education, AFQT and Black on Log Wages

	NLSY79		NLSY97	
Model:	(1)	(2)	(3)	(4)
Education	0.087***	0.077***	0.069***	0.068***
	(0.007)	(0.006)	(0.009)	(0.006)
Education × Potential Experience/10	-0.038**		-0.047***	
	(0.012)		(0.013)	
Education × Actual Experience/10		-0.023		-0.057***
		(0.014)		(0.015)
Standardized AFQT	0.030*	0.037**	-0.023	-0.014
	(0.015)	(0.013)	(0.017)	(0.013)
AFQT × Potential Experience/10	0.066*		0.055	
	(0.027)		(0.030)	
AFQT × Actual Experience/10		0.062*		0.057
		(0.029)		(0.036)
Black	-0.031	-0.034	-0.100**	-0.090***
	(0.028)	(0.024)	(0.031)	(0.024)
Black × Potential Experience/10	-0.116*		0.024	
	(0.046)		(0.056)	
Black × Actual Experience/10		-0.096		0.027
		(0.053)		(0.073)
R^2	0.236	0.262	0.112	0.128
No.Observations	111708	111708	88524	88524
Years	1979-1988	1979-1988	1997-2008	1997-2008

Notes: The data are from the 1979-1988 waves of the NLSY79 and the 1997-2008 waves of the NLSY97. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

reveals a distinct pattern. The effect of AFQT on wage is initially not statistically different from zero, and increases insignificantly as workers acquire more experience. The time paths of the coefficient on education and AFQT provide empirical evidence for Altonji and Pierret (2001)'s hypothesis of employer learning and statistical discrimination, implying that the model of employer learning and statistical discrimination widely tested by the NLSY79 sample could also be applied to the young NLSY97 generation.

It is worth noting that the coefficients on the race indicator, *Black*, in column (2) and (4) reveal a very different story of racial statistical discrimination. In the NLSY79 sample, the coefficient on the race indicator, *Black*, is small in magnitude and not statistically significant. Altonji and Pierret (2001) also report that raical wage gap is not statistically different from zero at $t = 0$, and they conclude that there is no or very little statistical discrimination on the basis of race. In contrast, the coefficient of $-0.090(0.024)$ on *Black* shown in column (4) of Table 3.3 is negative and statistically significant, meaning that the wage of black workers is about 9 percent lower than that of their white counterparts at the time of initial entry into the labor market. The wide initial racial wage gap is a distinct feature of the NLSY97 sample, and provides strong evidence that employers use race as a cheap source of information and statistically discriminate against black workers in the NLSY97. The difference in the *Black* coefficient between these two samples suggests that racial statistical discrimination in the U.S. labor market becomes stronger over the past decades even though government has put into a lot of effort into reducing statistical discrimination against black workers. In the NLSY97, employers not only statistically discriminate among young workers on the basis of education, but also on the basis of race.

Earlier employer learning literature reports that various educational groups are likely to be associated with different patterns of employer learning process.[5] Our earlier research confirms that employer learning process varies between high school graduates and college graduates in the NLSY79. Following the literature, we distinguish between these two education groups to obtain more clear-cut results. In each sample, we apply the regression model (3.2) to high school graduates and college graduates separately, and present the regression results in Table 3.4. From this point on, actual experience will be used as our measure of experience since potential experience and actual experience give rise to qualitatively similar results and we actual experience is a more accurate measure of labor market experience.

The regression results presented in Table 3.4 indicate that Arcidiacono, Bayer, and Hizmo

[5]See Schonberg (2007) and Arcidiacono, Bayer, and Hizmo (2010).

Table 3.4: The Effects of AFQT and Black on Log Wages by Education

	NLSY79		NLSY97	
	High School	College	High School	College
Model:	(1)	(2)	(3)	(4)
Standardized AFQT	0.019	0.108**	-0.027	0.078**
	(0.017)	(0.034)	(0.016)	(0.030)
AFQT × Actual Experience/10	0.099**	0.061	0.127*	-0.151
	(0.037)	(0.087)	(0.057)	(0.096)
Black	-0.069*	0.093	-0.090*	-0.022
	(0.031)	(0.069)	(0.035)	(0.074)
Black × Actual Experience/10	-0.073	0.055	0.071	-0.267
	(0.068)	(0.159)	(0.123)	(0.255)
R^2	0.190	0.183	0.104	0.078
No.Observations	59304	17076	35496	13932
Years	1979-1988	1979-1988	1997-2008	1997-2008

Notes: The data are from the 1979-1988 waves of the NLSY79 and the 1997-2008 waves of the NLSY97. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(2010)'s finding that productivity is gradually revealed for high school graduates but directly observed for college graduates holds for both the NLSY79 and NLSY97 generations. In each sample, we observe non-significant coefficient on AFQT score and large coefficient on AFQT interacted with experience for high school graduates, and large coefficient on AFQT score and non-significant coefficient on AFQT-experience interaction term for college graduates. The employer learning process plays a very limited role in the college market since college graduates are paid based on their productivity from the beginning of their careers.[6] In other words, the model of employer learning and statistical discrimination is only applicable to the group of high school graduates. For this reason, we will focus on the regression results for high school graduates.

In the high school market, employers initially put very little weight on AFQT, and gradually increase the weight as worker gains more experience. Furthermore, employers make full use of racial information to infer worker's productivity. The racial wage gap is initially negative and significant, implying that *Black* acts as a hard-to-observe characteristic in the wage regression. Therefore, employers rely on race to determine wage at the time of initial hire,

[6]Arcidiacono, Bayer, and Hizmo (2010) find that there is an initial wage premium for college-educated black in the labor market, and our regression results shown in column (2) of Table 3.4 confirm this finding for the NLSY79 generation. In the NLSY97, however, we do not observe the existence of initial black wage premium in the college market.

and make more informed wage decision as they gradually learn about the productivity.

By comparing the results presented in column (1) and (3), we find that AFQT and *Black* have a steeper profile with experience in the NLSY97 than in the NLSY79. While the coefficients on *AFQT* and *Black* interacted with experience are not significant, the coefficient on AFQT-experience interaction term is 0.127(0.057) in the NLSY97 compared with 0.099(0.037) in the NLSY79, and the coefficient on *Black* is more negative in the NLSY97 than in the NLSY79. The distinction between these two generations implies that the NLSY97 high school graduates face stronger employer learning and statistical discrimination than the elder NLSY79 generation. For this reason, the NLSY97 generation may be a good candidate for the study of the influencing factors of employer learning and statistical discrimination.

In this chapter, we will focus on the NLSY97 black high school graduate to explore the influencing factors of employer learning and statistical discrimination. Our regression results presented in Table 3.4 indicate that race plays a role similar to education in the wage determination process of high school graduates in the NLSY97. In the high school market where worker's productivity is not directly observable, employers rationally use race and education as cheap sources of information to evaluate the productivity of their workers, and make the wage decision accordingly. Black high school graduates are one of the most disadvantaged group in the labor market because of the combined discrimination based on race and discrimination based on educational level. Double discrimination against black high school graduates make this group an ideal subject of our analysis. The NLSY97 also has one advantage over the NLSY79 that it contains detailed information about employer-specific characteristics, such as demographic information of supervisors, industry, occupation, region of residence, and also firm size indicators. In the following empirical analysis, we analyze how these employer-specific factors affect black high school graduates, and provide some insights into the possible influencing factors of employer learning and statistical discrimination.

3.3.2 Supervisor-Worker Race Match

In the previous section, we find that statistical discrimination on the basis of race does exist in the labor market for the young NLSY97 generation. Consequently, a question of increasing interests is whether sharing the same race with the supervisor will reduce statistical discrimination. Black workers might be at a disadvantage in revealing their skills to their white employers because of the existence of cultural and language barriers between blacks and whites. The literature in social psychology and sociology believes that culture plays a fundamental role in interpersonal communication and evaluation. People who grow up under similar environments are likely to share a common framework to evaluate each other's productivity. Therefore, employers may assess the productivity of workers more accurately when the workers being considered have a similar cultural background. Cornell and Welch (1996) shows how discrimination can occur when cultural similarity makes it easier to judge job applicants' unknown qualities. Their model is based on the assumption that there are no average differences between people of various types and employers do not prefer job candidates from similar backgrounds. In this section, we will use the NLSY97 data to test the proposition that having the same race with the supervisor will reduce employer learning and statistical discrimination since employers are better able to evaluate the productivity of workers with the same race.

Some studies in the literature have explored the role of supervisor's race in worker's employment outcomes. Giuliano, Levine, and Leonard (2006) use daily personnel records from a large U.S. retail firm and report that racial differences between manager and employee affect three employment outcomes: quits, dismissals, and promotions. They find that black employees are no more likely to quit when they have a different-race manager, but they are more likely to be fired and less likely to be promoted. Using the same NLSY97 data, Fadlon (2010) examines the impact of supervisor's race from the perspective of statistical discrimination and employer learning, and find some support for the argument that employers statistically discriminate less against workers who share the same race than workers who does not share the same race.

Table 3.5: Employer-Worker Race Match and Mismatch

	No. Obs.	Race Match	Race Mismatch
White	59,860	95.98%	4.02%
White High School Graduate	24,032	95.97%	4.03%
White College Graduate	10,880	95.15%	4.85%
Black	20,916	42.29%	57.71%
Black High School Graduate	8,391	43.68%	56.32%
Black College Graduate	1,970	37.36%	62.64%

Notes: The data are from the 1997-2008 waves of the NLSY97. Race match occurs when supervisors and workers share the same race, white workers with white supervisors or black workers with black supervisors. Race mismatch occurs when supervisors and workers do not share the same race, white workers with black supervisors or black workers with white supervisors.

Table 3.5 shows the racial match information between employers and workers in our NLSY97 sample. The proportion of race match for white workers, white workers with white supervisors (95.98%), is very high compared with race match for black workers, black workers with black supervisors (42.29%). White workers are mainly employed by white supervisors regardless of the educational level. These statistics are consistent with Giuliano, Levine, and Leonard (2009)'s finding that non-black mangers hire more whites and fewer blacks than do black managers.[7] Fadlon (2010) also reports that white workers are more likely to work for white supervisors.

Taking the small percentage of black supervisors (13.93%) in the labor market into consideration, the supervisor-worker race match rate for black workers (42.29%) implies that black workers are more likely to pair with black supervisors. Recent studies have consistently found that black employers hire more black workers than white employers. Stoll, Raphael, and Holzer (2004) suggest two possible reasons for the pattern: black employers receive a great rate of job applications from black workers than do white employers, and they hire a great proportion of black job applicants. However, it is worth noting that it might be difficult for black workers to find a match employer since the labor market is dominated by white supervisors.[8]

Will race similarity between supervisor and worker help employers better understand the productivity of black high school graduate and reduce the employer learning and statistical discrimination against them? To provide an answer to this question, we will incorporate supervisor's race into the model of employer learning and statistical discrimination in this section. It is interesting that the race match rate (43.68%) for black high school graduate is much larger than that for black college graduate (37.36%). As we discussed earlier, college graduation helps workers directly reveal their productivity, so communication issues between black and white might be a less severe problem for black college graduates.

We firstly examine how racial difference between employer and workers affects employer learning process of black high school graduates. The group of black high school graduates are divided into two subsamples, race match sample and race mismatch sample. In the race match sample, black high school graduates are employed by black supervisors while race mismatch sample consists of black high graduates with white supervisors. The sample size

[7]Giuliano, Levine, and Leonard (2009) use personnel data from a large U.S. retail firm to examine how the race of supervisor affects the racial composition of new hires. Their results suggest that supervisor race is an important determinant of the racial composition of new hires even though characteristics of the workplace and its location are the primary determinants.

[8]The proportion of white supervisor in our sample is 86.07% as opposed to 13.93% of black supervisors.

for each subsample, 3622 for the race match sample and 4606 for the mismatch sample, is large enough for our empirical analysis.

Table 3.6: The Effects of AFQT on Log Wages by Supervisor-Worker Race Match

	Race Match		Race Mismatch	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.105	0.063	0.114**	-0.021
	(0.073)	(0.073)	(0.043)	(0.049)
AFQT × Experience/10		0.141		0.469**
		(0.375)		(0.166)
R^2	0.075	0.076	0.200	0.226
No.Observations	3622	3622	4606	4606

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression results for the race match sample and the race mismatch sample are presented in Table 3.6. As we can see from columns (1) and (3), the impact of AFQT score on wage is substantial and significant. For black high school graduates, a one standard deviation increase in AFQT score is associate with about 11% increase in wage. In columns (2) and (4), we add the AFQT-experience interaction term into the regression to learn the experience profile of the return to AFQT. The comparison between these two columns shows that AFQT has a much steeper profile with experience in the race mismatch sample than in the race match sample. In the race mismatch sample, the coefficient on AFQT is small and statistically insignificant, and the coefficient on AFQT interacted with experience is positive and statistically significant. When black high school graduates pair with white supervisors, the return to AFQT is very limited upon initial entry into the labor market, but increases sharply as workers gain experience. On the other hand, the AFQT-experience profile in the race match sample exhibits high intercept and flat slope, implying that the return to AFQT is initially high and rises gradually over time.

The difference in AFQT-experience profiles between the race match sample and the race mismatch sample indicates that supervisor's race does have a great influence on the employer learning process of black high school graduates. The race match sample and the race mismatch sample are associate with different patterns of employer learning. In the race match sample, black supervisors could directly learn some parts of productivity upon labor market entry, and continue to learn additional information over time. In the race mismatch sample, however, white supervisor have very limited information on the productivity of black high school graduate at the time of initial hire, and the learning takes place mainly after hire.

After confirming that supervisor-worker race match does significantly impact the employer learning process of black high school graduates, we will turn to the issue of statistical discrimination on the basis of race. We are interested in whether sharing the same race with the supervisor will reduce racial statistical discrimination faced by black high school graduates. For the sake of comparison, the regression results for high school graduates in the NLSY97 presented in column (3) of Table 3.4 appear again in column (1) of Table 3.7. Now we restrict the sample to high school graduates, and perform a separate analysis for race match sample, white high school graduates with white supervisor and black high school graduates with black supervisor, and race mismatch high school sample, white high school graduates with black supervisor and black high school graduates with white supervisor.

Table 3.7: The Effects of Black on Log Wages by Supervisor-Worker Race Match

	High School Grad	RaceMatch	RaceMismatch
	(1)	(2)	(3)
Black	-0.090*	-0.030	0.003
	(0.035)	(0.059)	(0.090)
Black $\times$ Experience/10	0.071	-0.128	-0.156
	(0.123)	(0.219)	(0.250)
R^2	0.104	0.086	0.206
No.Observations	35496	25998	5562

Notes: The sample is restricted to high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for AFQT score, AFQT score interacted with experience, urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

If race similarity between supervisor and workers does help reduce statistical discrimination based on race, we are expected to observe a narrow black-white racial gap in the case of supervisor-worker race match. In other words, the coefficients on *Black* and *Black* interacted with experience vary across different groups. As we have discussed, employers statistically discriminate against black high school graduates and pay them 9% less than white workers with similar qualifications. However, the coefficient on *Black* is not statistically significant either in the race match sample or the race mismatch sample. The results indicate that there is no significant difference in the extent of statistical discrimination between the group of white high school graduates with white supervisor and the group of black high school graduates with black supervisor. Likewise, white supervisors does not discriminate black high school graduates more than black supervisors discriminate white high school graduates. The substantial reduction in the coefficient on *Black* shown in Table 3.7 implies that black high school graduates are not in a disadvantaged position when they working for black supervisors as compared with white high school graduates having white supervisors. Taking the fact that black workers are associated with 9% wage loss into consideration, the finding that black and white high school graduates are discriminated to the same extent in the race match sample implies that working for a black supervisor could help black high school graduates reduce the racial statistical discrimination against them.

The regression results presented in Table 3.6 and 3.7 suggest that black supervisors are better equipped to assess the productivity of black workers. For black high school graduates whose productivity are not directly revealed to their employers, working for a supervisor with a different race makes the bad situation worse. The combined effects of the unobservable productivity and cultural and language barriers between black and white contribute to the double discrimination against black high school graduate.[9] Race match between supervisor and workers could reduce employer learning and statistical discrimination against black high school graduate. Using the same NLSY97 data, Fadlon (2010) also finds evidence that black employers statistically discriminate less against black workers.[10]

In this section, we analyze how supervisor's race affects the employer learning and statistical discrimination of black high school graduates. The differences in AFQT-experience profiles between the race match sample and the race mismatch sample indicate that the pattern of employer learning varies with the race of supervisor. Furthermore, the disadvantaged position of blacks in the high school sample and the equal position of blacks and whites in the race match sample imply that the extent of racial statistical discrimination is reduced when black

[9] The empirical results for black college graduates show that the influence of racial difference between supervisor and worker on the wage decision is negligible because college graduation enables black college graduate to perfectly reveal their productivity at the time of hire. Cultural and language barriers between black and whites seems to be a minor concern for black college graduates. The analysis results are available upon request.

[10] Fadlon (2010) further examines whether or not the probability of working for a match employer is positively correlated with AFQT score. If black employers better observe the underlying productivity of black workers, then high skill workers should prefer to work for a match employer that could better evaluate their productivity. His results show strong selection of white workers to white employers regardless of the productivity level, but find little evidence that black workers with high productivity select themselves to black employers. Fadlon (2010) explains that there are not enough black employers that offer high skill jobs in the labor market.

workers working for black supervisors. To summarize, working for a black supervisor could reduce employer learning and statistical discrimination against black high school graduates since black supervisor are better able to learn the productivity of black workers as compared with white supervisors.

3.3.3 Supervisor Age

Another factor that might influence employer learning and statistical discrimination is supervisor's age. Old and experienced supervisors are expected to be more capable of evaluating the productivity of their subordinates. Traditionally, managers tend to be older and more experienced than most of the workers they supervise. However, it is now very common to find old workers reporting to younger managers. Previous studies in the literature have examined the relationship between supervisor's age and important labor market outcomes. Giuliano, Levine, and Leonard (2006) find that age differences do have some influences on worker's employment outcomes even though race differences produce the largest effects. Age differences exert no impact on quits or promotions, but they do affect dismissals. More specifically, workers are more likely to be dismissed if they are at least 20 percent younger than their managers, but are less likely to be dismissed if they are at least 20 percent older than their managers.

Table 3.8: Summary Statistics for Supervisor's Age

	No. Obs	Median	Mean	Std.Dev	Min	Max
Supervisor Age	7542	40	39.08	9.93	20	71

Notes: The sample is restricted to black high school graduates in the NLSY97.

The NLSY97 contains detailed demographic information about worker's supervisors, such as age, gender and race, and we will focus our attention on the age of supervisor in this section. Table 3.8 shows the summary statistics for the age of employers who manging black high school graduates. In our sample of black high school graduate, the age of supervisors ranges from 20 to 70, and the mean age (39.08) and the median age (40) are very close to each other. We use the median age 40 to divide the sample into two groups, the group of workers with supervisors under the age of 40, and the group of workers with supervisors at the age of 40 or above.[11]

[11]We concentrate on the age of supervisor rather than the age difference between supervisor and their workers in the empirical analysis. However, the analysis results should not vary much between these two

Table 3.9: The Effects of AFQT on Log Wages by Supervisor's Age

	Old Supervisor		Young Supervisor	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.150*	0.037	0.083	-0.035
	(0.062)	(0.065)	(0.046)	(0.053)
AFQT × Experience/10		0.338		0.446*
		(0.174)		(0.204)
R^2	0.134	0.142	0.140	0.162
No.Observations	3675	3675	3694	3694

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We repeat the regression analysis for these two supervisor age groups separately, and present the analysis results in Table 3.9. Again, AFQT score has a significant effect on the wage determination of the NLSY97 generation.[12] A one-standard deviation increase in AFQT score is associated with 8.3% to 15% wage raise. To explore the relationship between supervisor's age and the employer learning process, we compare the difference in the AFQT-experience profile between the old supervisor sample (supervisor age >= 40) and the young supervisor sample (supervisor age < 40). In both samples, AFQT exhibits a steep profile with experience relative to AFQT-experience profile shown in the race match sample, suggesting that supervisor's race plays a much more important role than supervisor's age does in the employer learning process. Regardless of the supervisor's age, it takes employers a while to fully understand the productivity of their workers. However, the comparison between these two sets of regression coefficients shown in column (2) and column (4) of Table 3.9 indicates that supervisor's age does influence the employer learning process of black high school graduates.

It is clear from Table 3.9 that the AFQT-experience profile is steeper in the young supervisor sample than in the old supervisor sample. In the young supervisor sample, the return to AFQT is not significantly different from zero at the time of labor market entry, and raises by 44.6% after ten years. On the other hand, the impact of AFQT score on the wage of workers who have a supervisor at the age of 40 or above is initially 3.7% and increases an additional

different measures due to the narrow age range of the NLSY97 generation.

[12]In column (3) of Table 3.9, the coefficient of 0.083(0.046) on AFQT is slightly significant at the 10% significant level.

33.8% after workers gain 10 years of experience.[13] The difference in the AFQT-experience profiles implies that old supervisors could directly learn some parts of worker's productivity at the time of initial hire even though most parts of learning take place after hire while young supervisors are only capable of learning worker's productivity after workers start the job.

Table 3.10: The Effects of Black on Log Wages by Supervisor's Age

	High School Grad	Old Supervisor	Young Supervisor
	(1)	(2)	(3)
Black	-0.090*	-0.086	-0.099*
	(0.035)	(0.057)	(0.043)
Black × Experience/10	0.071	-0.008	0.178
	(0.123)	(0.174)	(0.156)
R^2	0.104	0.116	0.099
No.Observations	35496	16152	12578

Notes: The sample is restricted to high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for AFQT score, AFQT score interacted with experience, urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To investigate the issue of statistical discrimination, we pool white and black high school graduates together, and then apply the same criterion to split the sample into two groups by supervisor's age. The results for these two groups, the group of old supervisor and the group of young supervisor, are presented in columns (2) and (3) of Table 3.10. We are mainly interested in coefficients related to race, and focus our discussion on the coefficient on *Black* since the coefficient on *Black* interacted with experience is not statistically significant in all three samples. When high school graduates are employed by supervisors at the age of 40 or above, the white-black wage gap is smaller, reducing from 9% to 8.6%. In contrast, the racial wage gap increases to 9.9% in the sample of young supervisor where supervisors are less than 40 years old. The change in the coefficient on *Black* implies that racial statistical discrimination against black high school graduates becomes weaker when they are managed by older and experienced supervisors.

The analyses results demonstrate that supervisor's age is also an important factor that influences employer learning and statistical discrimination. Old supervisors may learn from their previous interactions with black workers, and acquire good judgment about the productivity of black workers. They are able to directly learn some parts of productivity when workers

[13] In the old supervisor sample, the coefficient on AFQT-experience interaction term, 0.338(0.174), is significant at the 10% significant level.

enter the labor market, and put more weight on true productivity and less weight on racial information in the wage decision. Working for a supervisor at the age of 40 or above could reduce employer learning and statistical discrimination against black high school graduates.

3.3.4 Firm Size

In the previous two sections, we examine how demographic information of supervisors including race and age could affect employer learning and statistical discrimination of black high school graduates. Our group of interest, black high school graduates, may also be influenced by firm-specific characteristics. In the NLSY97, individuals provide information about the firm they working for, such as the number of employees in the firm. In this section, we will analyze the role of firm size in employer learning and statistical discrimination.

Most big companies pay efficiency wage to attract the best talent since they demand workers of high productivity.[14] Moreover, they receive thousands of resumes for each job posting, and usually follow standard hiring procedures to hire the best candidates. In contrast, small firms are typically less bureaucratic, and are more careful when hiring employees. They offer a less formal and more personal working environment, and the interpersonal relationships between senior management and employees are better. Ferrer and Lluis (2008) find that firms of different sizes reward unmeasured ability differently. In particular, the returns to unmeasured ability are lower in large firms than in medium-sized firms. A possible explanation is that monitoring costs result from the large firm size may prevent large firms from rewarding ability directly through wages.

Table 3.11: Summary Statistics for Firm Size

	No. Obs	Median	Mean	Std.Dev	Min	Max
Firm Size	7410	35	389.01	1627.49	1	18000

Notes: The sample is restricted to black high school graduates in the NLSY97.

We use the number of employees working for the firm as our indicator of firm size. As shown in Table 3.11, the number of employees in the firm varies greatly in the sample of black high school graduates, and the median number of employees is 35. The median number is used to split the sample of black high school graduate into two groups, the group of medium-large

[14]Studies on a number of different countries and time periods have reported that big firms pay more than small firms, and the size-wage effect is substantial. See Oi and Idson (1999) for an exposition of the firm size-wage literature.

firm where the number of employees in the firm is equal to or greater than the median number 35,[15] and the group of small firm where the number of employees in the firm is less than the median number 35. We apply the model of employer learning and statistical discrimination to each group, respectively, and compare the regression results to investigate the effect of firm size.

Table 3.12: The Effects of AFQT on Log Wages by Firm Size

	Small Firm		Medium-Large Firm	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.147*	0.030	0.092	-0.087
	(0.058)	(0.052)	(0.051)	(0.077)
AFQT × Experience/10		0.437		0.561*
		(0.231)		(0.252)
R^2	0.170	0.182	0.164	0.207
No.Observations	3517	3517	3740	3740

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression results presented in Table 3.12 are qualitatively similar to those presented in Table 3.9. In each sample, the impact of AFQT on the wage of black high school graduates is large and statistically significant,[16] and AFQT has a steep profile with experience demonstrated by the small coefficient on AFQT and the large coefficient on AFQT interacted with experience. The productivity of workers is gradually revealed to their employers whether they working for a medium-large firm or a small firm.

By comparing the time path of the impact of AFQT on log wage in these two groups, we find that the pattern of employer learning does vary with the firm size. In small firms where employers and workers are more likely to have a close interpersonal relationship, employers seems to be able to learn some parts of worker's productivity directly through the information obtained from hiring process. After hire, employers continue to learn worker's productivity from newly acquired information. As shown in column (2) of Table 3.12, for black high school graduates who working for a small firm, the initial returns to AFQT is relatively small, but increase by 43.7% after 10 years in the labor market. In contrast, employers in medium-large

[15] Because of the sample size limitation, we do not distinguish between medium-sized firm and large firm in the empirical analysis.

[16] In the big firm sample, the coefficent of 0.092(0.051) is significant at the 10% significance level.

sized firms have very limited information about worker's productivity when workers begin the job, and only start to learn the productivity of their workers after hire.

Table 3.13: The Effects of Black on Log Wages by Firm Size

	High School Grad	Small Firm	Medium-Large Firm
	(1)	(2)	(3)
Black	-0.090*	-0.079	-0.136**
	(0.035)	(0.060)	(0.050)
Black × Experience/10	0.071	0.054	0.122
	(0.123)	(0.212)	(0.162)
R^2	0.104	0.118	0.106
No.Observations	35496	14745	13230

Notes: The sample is restricted to high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for AFQT score, AFQT score interacted with experience, urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.13 shows how firm size affects white-black wage gap of high school graduates. The racial wage gap is 7.9% in small-sized firms, and 13.6% in firms of medium-large size, compared with 9% in pooled sample. The reduced wage gap between whites and blacks in the sample of small firms provide evidence in support of weaker statistical discrimination on the basis of race in small-sized firms. In high school market where worker's productivity is not directly observable, small firms rely less on racial information to evaluate productivity, and thus discriminate less against black workers. It is not surprising that small firms put less weight on race in wage decision since the analysis of employer learning reveals that they are able to directly some parts of worker's productivity. In medium-large firms, racial information is more important due to the unobservability of productivity.

The extent of employer learning and statistical discrimination associated with firms of different sizes suggests that working for a small firm could help black high school graduates directly reveal parts of their productivity even though employers will need their job performance information to learn most parts of their productivity. Black high school graduates will be better off if they choose to work in a small firm.

3.3.5 Potential Factors

In addition to the above three factors, supervisor's race, supervisor's age, and firm size, we also investigate the effects of supervisor's gender (Female or Male), worker's union status (Union or Nonunion), worker's occupation (White collar or Blue collar) and worker's region of residence (South or Non-south). The regression results are presented in the Appendix. However, we are not able to draw any definite conclusion regarding the effect of these factors on employer learning and statistical discrimination in the black high school market.

Beside racial difference and age difference, Giuliano, Levine, and Leonard (2006) also examine the role of gender difference between supervisor and worker in worker's employment outcomes. They find that gender difference has a small effect on quit rates but does not affect dismissals or promotions. Of particular note is that females comprise 70 percent of employees and around 80 percent of managers in their sample. In contrast, females only comprise 21.03% of supervisors in our sample of black high school graduates. The lack of female supervisors may be the reason that we do not find any significant effect of gender difference between supervisor and worker on the employer learning process. The regression results for the gender match and gender mismatch samples are presented in Table 3.14.

For most union members, wages are predetermined, and it is worth investigating whether the pattern of employer learning process varies between union members and non-union members. Hirsch (2004) provides a good summary of studies that emphasized the effects union have on productivity. The percentage of black high school graduates belonging to a union in our sample is 17.43%, and we are unable to draw any definite conclusion regarding the effect of union membership on employer learning process. As we can see from Table 3.15, however, union members seem benefit more from having higher productivity than non-union members do since the impact of AFQT score on wage is much larger for union members.

The pattern of employer learning is likely to be different between different types of workers and jobs. Mansour (2012) provides several pieces of evidence that the pattern of employer learning varies significantly across occupation using the NLSY79 and CPS data. A possible explanation is that non-random occupational sorting may lead to differences in the variance of worker's productivity or the speed at which employers learn. Workers could be broadly classified into blue-collar and white-collar workers. The productivity of blue-collar workers should be easier to observe than white-collar workers because blue-collar workers usually use physical work to produce tangible goods while white-collar workers perform professional work in an office setting. On the other hand, employers are more carefully about the hiring of white-collar workers since such jobs require high skill levels and pay well, so they should have more information about the productivity of white-collar workers compared with blue-collar workers at the time of hiring. Bauer and Haisken-DeNew (2001) use a large German panel data set and find that employer learning in Germany takes place only for blue-collar workers at the lower end of the wage distribution. By differentiating blue-collar and white-collar workers and estimating the wage regressions separately, however, we do not find any empirical evidence that occupation affects the employer learning process of black high school graduates.[17]

Black population has the highest concentration in the south. The 2010 U.S. census showed that 50% of the black lived in the south and 105 southern counties had a black population of 50% or higher. In our sample of black high school graduates, 61.5% of black workers live in the south. And the black comprise 45.38% of high school graduates in the south and 16.68% in the non-south. The high concentration of blacks in the south leads to the question that whether employers are better equipped to evaluate the productivity of black workers in black-dominated communities. Giuliano, Levine, and Leonard (2009) examine the effects of manager race on the racial composition of new hires by geographic locations. They find that the differences between the hiring patterns of non-black managers and black managers are especially large in the south. Bertrand and Mullainathan (2004) also analyze the effect of employer location on discrimination, and report that employers located in more African American neighborhoods are slightly less likely to discriminate in Chicago. Using the NLSY97 data, however, we find that the contribution of region of residence to the employer learning process is not significant.

To summarize, we examine various demographic variables of supervisors and firm-specific characteristics, and find that supervisor-worker race match has the largest impact on the em-

[17]While collar occupations include executive, administrative and managerial; management related; mathematical and computer scientists; engineers, architects, and surveyors; engineering and related technicians; physical scientists; social scientists and related workers; life, physical, and social science technicians; counselors, social, and religious workers; lawyers, judges, and legal support workers; teachers; education, training, and library workers; entertainers and performers, sports and related workers; media and communication workers; health diagnosis and treating practitioners; health care technical and support; sales and related workers; office and administrative support workers. Blue collar occupations include protective service; food preparations and serving related; cleaning and building service; entertainment attendants and related workers; funeral related occupations; personal care and service workers; farming, fishing, and forestry; construction trades and extraction workers; installation, maintenance, and related workers; production and operating workers; food preparation; setter, operators, and tenders; transportation and material moving workers.

ployer learning and statistical discrimination process of black high school graduates. Working for a black supervisor could help black high school graduates directly reveal some parts of their productivity to the labor market, and thus reduce the employer learning and statistical discrimination against them. The age of supervisor and the firm size also affect how employers learn about worker's productivity. Black high school graduates face less employer learning and statistically discrimination if they work for an old supervisor or in a small firm. Earlier literature suggests that gender difference between the supervisor and worker, and union status, occupation and region of residence of worker may also play a role in the process of employer learning and statistical discrimination, however, we are not able to reach a conclusion in terms of the effect of these factors using the NLSY97 data.

3.4 Conclusion

In this chapter, we test the hypothesis of employer learning and statistical discrimination for both the NLSY79 and NLSY97 generations, and take a further look at the employer learning and statistical discrimination of black high school graduates in the NLSY97. There is a large body of empirical research exploring the employer learning and statistical discrimination of the NLSY79 generation, but only very few studies focus their attention on the young NLSY97 generation. In the NLSY97 data, respondents are relatively young, and are in early stages of career development. One advantage that the NLSY97 has is the large amount of background information on worker's supervisor and the firm they working for, which enables us to empirically analyze the effect of various factors that may play a role in employer learning and statistical discrimination.

We perform a separate analysis for the NLSY79 and NLSY97 generations, and confirm the existence of employer learning process in the NLSY97 as in the NLSY79. Employers gradually learn about worker's productivity, and rely more on true productivity in wage decision. A unique feature of the NLSY97 sample is that we also find strong empirical support for statistical discrimination on the basis of race. In the NLSY97, rational employers not only use educational level but also use racial information to infer worker's unobservable productivity. On the contrary, racial statistical discrimination is absent in the NLSY79 data.

Repeating the analysis for high school graduates and college graduates separately, we confirm the existence of perfect ability revelation associated with college graduates. Using the

NLSY79 data, a lot of studies provide empirical evidence in support of the proposition that college graduation helps workers directly reveal their productivity to the labor market. Our empirical analysis shows that the proposition also holds for the young NLSY97 generation. Employers gradually learn the productivity of high school graduates, but directly learn most parts of productivity of college graduates. Double discrimination, the combined discrimination based on education and discrimination based on race, make black high school graduates one of the most disadvantage group in the labor market. Compared with the NLSY79 generation, high school graduates in the NLSY97 face stronger employer learning and statistical discrimination, making the NLSY97 generation a better subject of our investigation.

The employer learning and statistical discrimination process is most important for high school graduates, so we focus on black high school graduates in the NLSY97 to evaluate potential influencing factors of employer learning and statistical discrimination. The investigation of various employer-specific characteristics reveals three important factors, the supervisor-worker race match, supervisor's age and firm size. Black high school graduates could reduce employer learning and statistical discrimination against them by working for a black supervisor, working for an old supervisor or working in a firm of small size.

In a world where worker's true productivity is not easily observable, black supervisors are better equipped to evaluate the productivity of black high school graduates. Similar backgrounds between supervisors and workers make communication easier and smoother. While supervisor-worker race match plays the most vital role in employer learning and statistical discrimination, the age of supervisor and the firm size also exert some impacts and influence the extent of employer learning and statistical discrimination. Old supervisors usually have many years of management experience, and have a good judgment about the productivity of their workers. And in small firms, supervisors are more likely to have a close working relationships with their subordinates, and base their evaluation of productivity on richer information.

In this chapter, we study the employer learning and statistical discrimination of black high school graduates under the basic assumption that employer learning is symmetric in the labor market, that is, both current firm and outside firms share the same information about worker's productivity. There is an extensive literature empirically tests whether employer learning is symmetric or asymmetric with the NLSY79 data. Asymmetric employer learning implies that current firm have access to richer information about worker's productivity compared with outside firms. Many studies find empirical evidence in favor of asymmetric employer learning in the labor market.[18] Our earlier research confirm that employer learning is mainly asymmetric for high school graduates in the NLSY79 data. If employer learning is asymmetric rather than symmetric for black high school graduates, there will be more scope for statistical discrimination. One direction for future research is to investigate the nature of employer learning in the NLSY97 sample, and examine how various factors affect employer learning and statistical discrimination under the suitable framework. The assumption of symmetric learning may diminish the impact of influencing factors if employer learning is actually asymmetric for high school graduates in the NLSY97.

We focus our analysis on the NLSY97 generation in this chapter because the NLSY97 data contains detailed demographic information about worker's supervisors. However, the NLSY97 is a relatively short sample, and all respondents are in their early stages of career development. In our sample, an average black high school graduates have less than 3 years of labor market experience. The influence of other factors such as occupation is not significant in our sample. A possible explanation is that respondents in the NLSY97 are very young and have very limited work experience. Our analysis will provide more insights into the influencing factors of employer learning and statistical discrimination as career of the NLSY97 generation evolves.

[18]See Bauer and Haisken-DeNew (2001), Schonberg (2007) and Pinkston (2009).

3.5 Appendix A

Table 3.14: The Effects of AFQT on Log Wages by Supervisor's Gender

	Gender Match		Gender Mismatch	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.093*	-0.022	0.141*	0.008
	(0.041)	(0.046)	(0.059)	(0.057)
AFQT × Experience/10		0.387*		0.525**
		(0.173)		(0.170)
R^2	0.128	0.141	0.163	0.198
No.Observations	6726	6726	1946	1946

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.15: The Effects of AFQT on Log Wages by Union Membership

	NonUnion		Union	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.116**	0.008	0.214*	-0.137
	(0.036)	(0.038)	(0.101)	(0.112)
AFQT × Experience/10		0.382**		0.968*
		(0.144)		(0.425)
R^2	0.135	0.151	0.205	0.264
No.Observations	7311	7311	1653	1653

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.16: The Effects of AFQT on Log Wages by Occupation

	White Collar		Blue Collar	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.116**	-0.002	0.121*	-0.005
	(0.041)	(0.054)	(0.056)	(0.050)
AFQT × Experience/10		0.411		0.440*
		(0.220)		(0.181)
R^2	0.353	0.371	0.086	0.101
No.Observations	2403	2403	5965	5965

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.17: The Effects of AFQT on Log Wages by Region of Residence

	NonSouth		South	
	(1)	(2)	(3)	(4)
Standardized AFQT	0.147**	-0.009	0.072	-0.044
	(0.054)	(0.048)	(0.042)	(0.050)
AFQT × Experience/10		0.518**		0.431*
		(0.197)		(0.178)
R^2	0.197	0.234	0.074	0.087
No.Observations	3768	3768	5988	5988

Notes: The sample is restricted to black high school graduates in the NLSY97. The experience measure is years of actual experience. All specifications control for urban residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 4

The Role of Verbal and Quantitative Skills in Wage Determination

(ABSTRACT)

This chapter investigates the associations between verbal and quantitative skills and individual earnings, and explores the employer learning process of these two specific types of skills. Using the NLSY79 data, we find that quantitative skills have a larger impact on wages compared with verbal skills even though both types of skills are important determinants of earnings. In the labor market, employers directly learn workers' verbal skills but gradually learn their quantitative skills. However, there are significant differences in both the rewards and employer learning process of verbal and quantitative skills between high school and college graduates. Verbal skills are more important than quantitative skills for high school graduates, whereas college-educated workers benefit greatly from having high quantitative skills but little from having high verbal skills. Furthermore, employers directly learn verbal skills and continuously learn quantitative skills in the high school market, but almost perfectly observe quantitative skills in the college market. Our analysis is a useful starting point for future discussion on the role of verbal and quantitative skills in the U.S. labor market.

4.1 Introduction

There is a growing interest in the labor market rewards to different types of cognitive skills, such as verbal comprehension and reasoning, and mathematic knowledge and skill, and writing skills. Foundational cognitive skills in reading, math, and writing are of central importance for success in career as well as in many aspects of life. Earlier literature reported that different types of skills are associated with varying wage returns. The contribution of basic cognitive skills as reflected in earning is an important research question to both economists and policy makers. Learning how different types of skills are rewarded in the labor market enhances economist's understanding of wage determination. For policy makers, knowing the relationship between labor market outcomes and different types of skills help them to better design training programs which aim at improving the basic skills of low-skilled workers.

Highly educated people generally have better labor market outcomes than less educated people. An important reason is that they are likely to have higher verbal and quantitative skills, which are key components of human capital and important drivers of economic growth. Verbal and quantitative skills appear to be a natural starting point for an investigation of the association between different types of skills and labor market outcomes, and are the focus of our research.

There exists a large and growing body of literature on the labor market returns to general cognitive ability[1] since Mincer (1958) and Becker (1964) developed the empirical foundations of human capital theory. However, there are relatively fewer studies in literature that analyze the role of specific types of cognitive skills in the wage determination of young workers. Examples of international studies that focus on verbal and quantitative skills include Murnane, Willett, and Levy (1995) and Dougherty (2003) with the U.S. data, McIntosh and Vignoles (2001) and Vignoles, Coulon, and Marcenaro-Gutierrez (2011) with the UK data,[2] Shomos (2010) with the Australian data, and Antoni and Heineck (2012) with the German data. In this chapter, we apply the framework of employer learning and statistical discrimination

[1] The recent literature on ability mainly focuses on cognitive skills and not socialization skills in analyzing the determinants of earnings due to the lack of appropriate data. It is common knowledge that both cognitive skills and social skills are related to socio-economic outcomes such as earning in the labor market. For example, Cawley, Heckman, and Vytlacil (2001) show that social skills have a strong effect on later earning by affecting educational attainment.

[2] See Grinyer (2006) for a useful summary of the current UK literature on how literacy and numeracy skills affect labor market outcomes.

developed by Farber and Gibbons (1996) and Altonji and Pierret (2001) to study the role of verbal and quantitative abilities in U.S. labor market. The motivation for this investigation lies in the increasing economic position of highly skilled workers over the past decades. To the best of my knowledge, this is the first study that examines the correlation between basic verbal and quantitative abilities and earnings from the perspective of employer learning and statistical discrimination.

In the model of employer learning and statistical discrimination, employers rely heavily on easy-to-observe characteristics at the time of hire, and gradually reduce their reliance on easy-to-observe characteristics and increase their reliance on hard-to-observe characteristics as new information becomes available. Most studies in the employer learning literature confirm Farber and Gibbons (1996) and Altonji and Pierret (2001)'s research finding that education is such an easily observable characteristic and worker's ability acts as a hardly observable characteristic in the model. The literature has not yet reached a consensus on the role of race since empirical studies provide mixed evidence.[3] While most researchers in the literature of employer learning focus their studies on general ability, the role of specific types of skills, such as verbal and quantitative skills, remains an under-researched area.

How basic cognitive skills and earnings interrelate is particularly important for low skilled workers who usually have low level of schooling and are the target group of government training programs. The literature has little to say about the returns to verbal and quantitative skills for this group. To address this issue, we investigate the extent to which verbal and quantitative skills matter for high school and college graduates, and fill a significant gap in the literature. Furthermore, a number of key studies on employer learning suggest that these two education groups are also likely to be associated with different employer learning processes. For example, Arcidiacono, Bayer, and Hizmo (2010) use a measure of general ability, and provide empirical evidence that ability is almost perfectly revealed for college graduates immediately upon entering the labor market, but is gradually revealed for high school graduates. This chapter contributes to the literature by examining the employer learning process of verbal and quantitative skills in both the high school and college markets.

[3] Altonji and Pierret (2001) find there is little evidence for statistical discrimination on the basis of race, and conclude that statistical discrimination plays a minor role in the racial wage gap. Similarly, Mansour (2012) confirms the absence of racial statistical discrimination in the labor market, but his empirical results imply that the extent of racial statistical discrimination might differ across occupations. In contrast, Arcidiacono, Bayer, and Hizmo (2010)'s results imply that employers statistical discriminate against black workers in the high school market.

In this chapter, we find that both verbal and quantitative skills are important determinants of earnings, and employers learn about these two kinds of basic skills differently. However, there are significant differences in both the rewards and employer learning process of verbal and quantitative skills between high school and college graduates. Specifically, using data from the NLSY79, we find that quantitative skills have a larger impact on wages compared with verbal skills, and that employers directly learn worker's verbal skills but gradually learn their quantitative skills. We perform a further analysis for two education groups, high school and college graduates, and the analysis results indicate that attending college does make a big difference in many ways. Verbal skills are more important than quantitative skills for high school graduates even though there are significant rewards to both types of skills. In contrast, college-educated workers benefit greatly from having high quantitative skills but little from having high verbal skills. Furthermore, employers directly learn verbal skills and continuously learn quantitative skills in the high school market, whereas they almost perfectly learn quantitative skills in the college market.

We make two main contributions to the literature. First, we investigate the associations between verbal and quantitative skills and individual earnings for two education groups, high school and college graduates, in the U.S. labor market. Second, we provide first empirical evidence on the employer learning process of two specific types of skills, verbal and quantitative skills.

The reminder of this chapter is as follows. Section 2 discusses the NLSY79 data and the econometric specifications we use for the empirical analysis. Section 3 presents our empirical findings for the overall sample as well as for different education groups. Section 4 draws conclusions and discusses directions for future work.

4.2 Data and Empirical Specification

4.2.1 NLSY79 Data

The data used in this empirical analysis are based on the 1979-2008 waves of the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative sample of young workers who were between 14 and 22 years old when first interviewed in 1979. We follow the criteria used in Altonji and Pierret (2001) and Arcidiacono, Bayer, and

Hizmo (2010) to select the sample. The empirical analysis is restricted to black and white male workers who have completed at least 9 years of education, and only include observations after the respondent has made the school-to-work transition. A respondent is considered to have entered the labor market when he has left school for the first time. Potential experience is the sum of months since the respondent first left school. Tenure and actual experience are calculated from the monthly work history data, which is constructed from the weekly work history data.[4] Tenure is computed as the number of months between the start of the job and either the date the job ended or the interview date, and actual experience is calculated as the sum of tenure for each job.

We use the the deflators from CPI-U released by Bureau of Labor Statistics to create real monthly wage with 1990 as the base year, and exclude all observations with real wages less than $1 or more than $100 from the analysis. The education variable is defined as the highest grade completed by the respondent at the time of interview. In the empirical analysis, we are particularly interested in two education groups, high school and college graduates, so we further split the sample into different groups according to the education level. High school graduates are defined as workers who have completed 12 years of schooling at the time of interview, and college graduates are workers who have at least 16 years of schooling.

The Armed Forces Qualification Test (AFQT) is widely used as a general measure of ability in the employer learning literature. AFQT score is a composite derived from select sections of the Armed Services Vocational Aptitude Battery (ASVAB) tests. The ASVAB is administered by the United States Military Entrance Processing Command, and is used to determine qualification for enlistment in the United States armed forces. It consists of a battery of 10 tests that measure knowledge and skills in various areas.[5] The original AFQT score in the NLSY79 data was constructed using the test scores on arithmetic reasoning, word knowledge, paragraph comprehension, and numerical operations. Starting from 1989, the numerical operations section was dropped from the AFQT score,[6] and the math knowledge score was included. The ASVAB is administered in 1980 to the NLSY79 respondents who were aged

[4]The work history data contains respondent's week-by-week labor force status. We transform each respondent's weekly work records into monthly ones, and build a complete employment history for each respondent in the sample by linking all the jobs across different survey years. Multiple jobs held at the same time are treated as a new job, and the average wage is calculated as the wage for the newly constructed job.

[5]The ASVAB tests include the following 10 sections: general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop information, mathematics knowledge, mechanical comprehension and electronics information.

[6]The numerical operations section had a design inconsistency. As a result, respondents received slightly different tests, and the completion rate differed slightly.

15 to 23. To compensate for the age difference, the AFQT scores were renormed controlling for age.

Our verbal and quantitative composite scores are computed in a way consistent with the construction of the AFQT score. We compute the verbal composite score by summing word knowledge (WK) and paragraph comprehension (PC) scores, and compute the quantitative composite score by summing the scores for arithmetic reasoning (AR) and math knowledge (MK). Our construction of verbal and quantitative composites is in line with Bishop (1992), who used the NLSY79 data to study the impact of academic competencies on wages. Dougherty (2003) is also concerned with the contributions of basic literacy and numeracy to earnings with the use of ASVAB test scores. He formed the verbal composite from word knowledge and paragraph comprehension, but only used arithmetic reasoning as the measure of numeracy skills. To make the effects of verbal ability and quantitative ability comparable to the effect of general ability documented in early literature, we standardize the verbal composite score and quantitative composite score to have a mean zero and a standard deviation of one for each three-month age group.[7]

Table 4.1: Summary Statistics

	Total	High School Grad	College Grad
Real Hourly Wage	1239.71	1013.86	1782.04
	(800.49)	(512.09)	(1079.08)
Potential Experience	135.94	140.74	123.51
	(84.92)	(86.31)	(79.44)
Actual Experience	111.10	112.97	108.08
	(74.96)	(76.28)	(71.98)
Education	13.41	12.00	16.72
	(2.28)	(0.00)	(1.17)
AFQT Score	0.252	-0.152	1.199
	(1.036)	(0.878)	(0.713)
Verbal Score	0.054	-0.277	0.812
	(1.017)	(1.012)	(0.508)
Quantitative Score	0.208	-0.194	1.177
	(1.053)	(0.862)	(0.801)
Black Porportion	0.29	0.33	0.17
No.Indiviudals	3234	1626	822
No.Observations	279598	130515	71103

Notes: The data are from the 1997-2008 waves of the NLSY79. Standard deviations are in parentheses. Real hourly wages are in cents. Potential experience and actual experience are in months.

The summary statistics for our NLSY79 male sample are presented in Table 4.1. It is not

[7]The NLS staff recommend using the AFQT-3 which is renormed within each three-month age group.

surprising that college graduates have relatively shorter work experience but earn much more than high school graduates. On average, a college graduate has 108 months of actual experience and earns an real hourly wage of \$17.82. For high school graduates, the average length of actual experience is 113 months, and the real hourly wage is \$10.14. In today's knowledge-based economy, the demand for skills is rising, and highly skilled workers are richly rewarded in the labor market. It is worth noting that there exists significant verbal and quantitative score gaps between high school and college graduates. The average verbal score of high school graduates is about one standard deviation lower than those of college graduates, and the average quantitative score difference between these two education groups is even larger, around 1.4 standard deviation. Therefore, college graduates generally have better verbal and quantitative skills than high school graduates. It is expected that, all else equal, people with high skills are more likely to attend and graduate from college.

4.2.2 Empirical Models

In this chapter, we apply the framework of employer learning and statistical discrimination developed by Farber and Gibbons (1996) and Altonji and Pierret (2001) to gain some understanding of the role of verbal and quantitative skills in wage determination. Of particular interest are the coefficients related to verbal and quantitative scores. How the impact of verbal and quantitative scores changes with experience will provide some insights into the employer learning process of these two types of skills.

We build upon the standard model of employer learning and statistical discrimination, and focus our attention on verbal and quantitative abilities rather than general ability. Therefore, verbal and quantitative scores enter the model as the measures of verbal and quantitative skills while most studies in literature use AFQT score as a measure of general ability. More specifically, we regress the log wages on education, verbal score, quantitative score, black indicator, the interaction terms between these variables and experience, and demographic variables such as region of residence and urban-rural residence. For the overall sample, the log wage equation is

$$\begin{aligned}\ln w_{i,t} =&\beta_0 + \beta_V Verbal_i + \beta_{V,t}(Verbal_i \times t_{i,t}) + \beta_Q Quant_i + \beta_{Q,t}(Quant_i \times t_{i,t}) \\ &+ \beta_{Black} Black_i + \beta_{Black,t}(Black_i \times t_{i,t}) + \beta_S S_i + \beta_{S,t}(S_i \times t_{i,t}) + \beta_\Omega \Omega_{i,t} + \epsilon_{i,t} \quad (4.1)\end{aligned}$$

where i is the individual index and t is the time index.

The model of employer learning and statistical discrimination has two empirically testable predictions. First, the coefficients on easy-to-observe characteristics will be initially large and decreasing over time, reflecting employer's decreasing reliance on these characteristics. Second, the coefficients on hard-to-observe characteristics will be relatively small at the beginning and raising over time as employers gradually increase the weight they put on these characteristics. In this chapter, we will concentrate on coefficients related to verbal and quantitative scores to learn the role of verbal and quantitative skills in wage determination as well as the employer learning process of these two types of skills. The magnitude of the coefficients on these two scores will reveal the part they play in the process of wage determination, and the time path of these coefficients will reflect the employer learning process of these two types of skills.

In the econometric model, our main coefficients of interest are the coefficient on verbal score, β_V, the coefficient on quantitative score, β_Q, the coefficient on verbal score interacted with experience, $\beta_{V,t}$, and the coefficient on quantitative score interacted with experience, $\beta_{Q,t}$. Large and significant coefficient on the test score-experience interaction term, $\beta_{V,t}$ or $\beta_{Q,t}$ implies a continuous employer learning process about worker's verbal or quantitative skills over their career development. In other words, employers can not accurately assess workers' skill level when they first enter the labor market, and gradually update their assessments using new information. If the coefficient on test score interacted with experience is small and insignificant, $\beta_{V,t}$ or $\beta_{Q,t}$, but that on verbal or quantitative test score, β_V or β_Q, is relatively big and significant, then little employer learning takes place after hire. In this case, employers have a good idea about worker's productivity at the time of labor force entry, and learn very little subsequently.

There is a large body of empirical evidence in the employer learning literature that the employer learning process differs across different education groups, such as high school and college graduates. For example, Arcidiacono, Bayer, and Hizmo (2010) provide evidence that employer learning process is most important for high school graduates since college degree helps college graduates directly reveal most parts of their abilities at the time of hire. Most of the research place great emphasis on worker's general ability, and study the employer learning process using measures of overall ability such as AFQT score. In this chapter, we contribute to the literature by analyzing the employer learning process of two certain types of skills, verbal and quantitative skills, for two education groups, high school and college graduates.

Following the literature, we split the sample into different groups by the level of education, and conduct the empirical analysis for high school and college graduates, respectively. The following regression model is applied to each group:

$$\begin{aligned}\ln w_{e,i,t} =& \beta_0^e + \beta_V^e Verbal_{e,i} + \beta_{V,t}^e (Verbal_{e,i} \times t_{e,i,t}) + \beta_Q^e Quant_{e,i} + \beta_{Q,t}^e (Quant_{e,i} \times t_{e,i,t}) \\ &+ \beta_{Black}^e Black_{e,i} + \beta_{Black,t}^e (Black_{e,i} \times t_{e,i,t}) + \beta_\Omega^e \Omega_{e,i,t} + \epsilon_{e,i,t}. \end{aligned} \tag{4.2}$$

where e is the education index that takes the value hs if the worker belongs to the group of high school graduates or col if the worker belongs to the group of college graduates.

Again, we are mainly interested in coefficients related to verbal and quantitative test scores, $\{\beta_V^e, \beta_{V,t}^e, \beta_Q^e, \beta_{Q,t}^e\}$, and also the differences in these coefficients between high school and college graduates, $\{\beta_V^{hs}, \beta_{V,t}^{hs}, \beta_Q^{hs}, \beta_{Q,t}^{hs}\}$ and $\{\beta_V^{col}, \beta_{V,t}^{col}, \beta_Q^{col}, \beta_{Q,t}^{col}\}$. Significant differences in the level of impact of verbal or quantitative skills on wages imply that this type of skills play a distinct role in the wage determination of high school and college graduates. If substantial differences exist between these two education groups in terms of the test score-experience profile, then employers learn about the verbal or quantitative skills of high school and college graduates differently. Our research differs from other studies in the sense that we investigate the role of verbal and quantitative skills under the framework of employer learning and statistical discrimination, therefore, we are able to provide more information regarding the importance of these skills.

4.3 Empirical Results

This section presents the main regression results. Our analysis starts with the investigation of the relationship between verbal and quantitative skills and labor market outcomes for the overall male sample. We are particularly interested in the groups of high school and college graduates, so we also repeat the analysis for these two groups. Specifically, we apply the regression model 4.1 to the overall male sample and the regression model 4.2 to two education groups. Actual experience is used as our measure of experience in the regression model since it more accurately captures worker's labor market experience compared with potential experience. The implied overall effects of verbal and quantitative scores reflect the importance of verbal and quantitative skills in wage determination, and the time paths of the impact of verbal and quantitative scores on wages provide some insights into the employer learning process of these two types of skills.

4.3.1 The Overall Sample

First of all, we investigate the labor market reward of verbal and quantitative skills for the overall male sample. The regression model 4.1 is applied to the overall male sample, and our focus of attention is the coefficients on verbal and quantitative scores as well as their interaction terms with experience. We are mainly interested in the level and the change rate of the influence of verbal and quantitative skills on worker's wage.

Table 4.2: The Effects of Verbal and Quantitative Abilities on Log Wages

	(1)	(2)
Verbal	0.052***	0.045***
	(0.010)	(0.012)
Verbal × Experience/10		0.008
		(0.010)
Quantitative	0.072***	0.051***
	(0.011)	(0.013)
Quantitative × Experience/10		0.023*
		(0.011)
Black	0.030	0.004
	(0.020)	(0.022)
Black × Experience/10	-0.084***	-0.056**
	(0.015)	(0.020)
R^2	0.382	0.382
No.Observations	277422	277422

Notes: All specifications control for education, education interacted with experience, urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) of Table 4.2 presents the estimation results of regressing the logarithm of hourly wages on verbal score, quantitative score, black, education, the interaction terms for black and education with experience as well as other controls for the overall male sample. It is clear that both verbal and quantitative skills have a large effect on earnings, and that the effect of quantitative ability on earnings is much larger than that of verbal ability. As shown in column (1), a one standard deviation increase in verbal score is associated with a 5.2% increase in earnings, and in the case of quantitative score, the same amount increase will lead to a 7.2% wage raise. Both the coefficients on verbal and quantitative scores are statistically significant at the 0.1% significant level, providing strong empirical evidence that verbal and quantitative skills play an important part in worker's wage determination.

Among all the studies that investigated the relationship between basic verbal and quantitative abilities and labor market outcomes, many of them reported that the economic returns to quantitative skills were more significant compared with those of verbal skills. McIntosh and Vignoles (2001) use the UK national child development study and international adult literacy survey data sets, and find evidence of a large and positive effect on earnings from having better quantitative skills. In the case of verbal ability, they find its effect is positive in one data set but not significant in the other data set. Using data from two longitudinal surveys of American high school seniors, Murnane, Willett, and Levy (1995) find that mathematical ability has a significant effect on wage while the effect of reading skills and vocabulary skills is not significant. A similar finding is also reported in Dougherty (2003) who use the same NLSY79 data as we do. In contrast to previous studies, Antoni and Heineck (2012) find there are significant payoffs to both literacy and numeracy and the payoff to numeracy is larger than the payoff to literacy in the German labor market.[8] Consistent with Antoni and Heineck (2012)'s findings, the regression results presented in Table 4.2 indicate that both verbal and quantitative abilities have a significant and positive effect on earnings even though the effect of quantitative ability is larger than that of verbal ability.

The second column of Table 4.2 presents the results of adding the interaction terms between verbal and quantitative abilities and experience to the specification. The inclusion of the verbal score interacted with experience slightly reduces the coefficient on verbal score from 0.052(0.010) to 0.045(0.012), and the coefficient of verbal-experience interactive variable, 0.008(0.010), is very small and not statistically significant. The coefficients of verbal score and verbal-experience interaction term suggest that the impact of verbal ability on earnings is initially large and do not change much over experience. Interpreted through the lens of employer learning theory, the verbal-experience profile implies that employers almost perfectly learn worker's verbal ability at the time of initial hire. Because of the prefect

[8]Furthermore, Antoni and Heineck (2012) examine potential heterogeneity in the rewards of literacy and numeracy between different groups, and do not find significant differences in the returns to these two basic skills by gender, and only small differences by migration background or by region.

revelation of verbal ability in the labor market, workers are paid in accordance with their verbal ability from the beginning of their careers.

The coefficients related to quantitative score shown in column (2) of Table 4.2 indicate that worker's quantitative ability affects earnings differently compared with verbal ability. The impact of quantitative ability on log wage is 5.1% at the time of labor force entry, and increases by an additional 2.3% as workers acquire 10 years of labor market experience. The growing impact of quantitative ability on earnings found in the wage regression implies that workers' quantitative skills are not perfectly revealed to the labor market when their career starts. At the time of initial hire, employers directly learn most parts of worker's quantitative ability from information accumulated during the hiring process, but they continue to learn as new information become available. Quantitative ability seems to be more difficult to observe than verbal ability in the labor market, and employers need more time and information to fully learn worker's quantitative ability.

In this section, we analyze the contributions of verbal and quantitative skills to earnings and the employer learning process of these two types of skills. It is clear that both verbal and quantitative skills are important and significant determinants of earnings even though quantitative ability has a larger impact on worker's wages than verbal ability. Furthermore, how the impacts of verbal and quantitative scores on wages change with experience implies that employer directly learn workers' verbal skills but gradually learn their quantitative skills. It requires more time and information for employers to fully understand the quantitative skills of their workers.

4.3.2 High School Graduates and College Graduates

The previous section does not distinguish among different education groups in the investigation of the association between verbal and quantitative abilities and labor market outcomes. An implicit assumption behind the analysis is that the impact of verbal and quantitative skills and their employer learning processes do not vary with education level. College graduates generally have better verbal and quantitative skills than high school graduates. As we discussed earlier, the average verbal score of college graduates are about one standard deviation higher than those of high school graduates, and the average quantitative score difference between these two education groups is even larger, around 1.4 standard deviation. It is very likely that these two types of skills benefit high school and college graduates differently. Furthermore, there is substantial evidence in the employer learning literature that high school and college graduates are associated with different employer learning processes. For these two reasons, we split the sample into different groups by education level, and focus our attention on high school and college graduates in this section.[9]

Table 4.3: The Effects of Verbal and Quantitative Abilities on Log Wages by Education

	High School Grad		College Grad	
	(1)	(2)	(3)	(4)
Verbal	0.071***	0.060***	0.019	-0.005
	(0.014)	(0.016)	(0.032)	(0.044)
Verbal × Experience/10		0.012		0.025
		(0.012)		(0.039)
Quantitative	0.045**	0.024	0.164***	0.143***
	(0.016)	(0.018)	(0.021)	(0.027)
Quantitative × Experience/10		0.022		0.025
		(0.014)		(0.025)
Black	0.003	-0.030	0.189***	0.158***
	(0.028)	(0.030)	(0.045)	(0.047)
Black × Experience/10	-0.049*	-0.014	-0.132***	-0.098*
	(0.020)	(0.025)	(0.034)	(0.039)
R^2	0.234	0.235	0.278	0.279
No.Observations	129915	129915	70335	70335

Notes: All specifications control for urban residence, region of residence, a cubic in experience and years effects. The numbers in parentheses are White/Huber standard errors accounting for multiple observations per person.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We apply the regression model 4.2 to high school and college graduates separately, and present the regression results in Table 4.3. By comparing regression coefficients between columns (1) and (3), we draw two important conclusions regarding the role of verbal and quantitative skills in wage determination. First, verbal ability has a greater effect than quantitative ability for high school graduates, but has a smaller effect with respect to college graduates. Second, quantitative ability is particularly important for college graduates. Our findings are generally consistent with Willis and Rosen (1979), who report that the effect of literacy is smaller than numeracy for higher-ability group but larger than numeracy for lower-ability group.

In the high school market, a one standard deviation increase in verbal score leads to a 7.1%

[9]Tyler (2004) tests the importance of basic cognitive skills for young dropouts who attempt General Educational Development (GED) exams. His results provide evidence that labor market also rewards the basic cognitive skills of students who may eventually drop out.

wage raise, and an increase of quantitative score by one standard deviation is only associated with a 4.5% increase in wage. A possible explanation is that high school graduates are more likely to be employed in low-skilled occupations where communication ability plays a more vital role than mathematic ability. In the case of college graduates whose verbal and quantitative abilities are more than one standard deviation higher than those of high school graduates, however, these two skills impact their wages very differently. The coefficient on verbal score is not statistically differently from zero, implying a relatively weak impact of verbal ability on the wage of college graduates. In contrast, the coefficient of 0.164(0.021) on quantitative score suggests that the return to quantitative ability is substantial and significant. Therefore, quantitative ability is an extremely important determinant of wage for college graduates who are usually employed in high-skilled professions.

To investigate the employer learning of verbal and quantitative abilities for our groups of interest, high school and college graduates, we add the linear interactions between experience and verbal and quantitative scores to the regressions in column (2) and (4) of Table 4.3. The coefficient of 0.060(0.016) on verbal score and the coefficient of 0.012(0.012) on verbal score interacted with experience presented in column (2) imply that the effect of a one standard deviation shift in verbal score is 0.060 when high school graduates enter the labor market, and that the effect does not change much as they accumulate more experience. In contrast, the coefficient on quantitative score decreases from 0.045(0.016) to 0.024(0.018) when the interaction term between quantitative score and experience is added between columns (1) and (2), and the coefficient of 0.022(0.014) on the interaction term is slightly significant at the 10% significance level. The implied effect of a one standard deviation increase in quantitative score on the earning of high school graduates increases by 0.022 during the first ten years in the labor market.

When high school graduates start their career, the verbal skills are almost perfectly revealed to the labor market, but the quantitative skills are only partially revealed. As new information becomes available after hire, high school graduates continue to reveal their quantitative skills to labor force participants. From the perspective of employer learning, employers are able to directly learn most parts of verbal skills of high school graduates but only some aspects of their quantitative skills based on information obtained from the interview process. After hire, employers will continue to learn their quantitative skills and gradually increase the weight put on quantitative skills when setting the wage. In other words, it takes employers some time to fully understand the quantitative skills of high school graduates.

As shown in column (4) of Table 4.3, both the effect of verbal score and the interactive effect between verbal score and experience level are small and statistically insignificant in the college market, providing further evidence that verbal ability is not as important as quantitative ability for college-educated workers. And the fact that the inclusion of quantitative score-experience interaction term, whose coefficient is not statistically significant, only slightly reduces the coefficient on quantitative score from 0.164(0.021) to 0.143(0.027) suggests that the quantitative skills of college graduates are almost fully rewarded upon initial entry into the labor market.

The regression results for college graduates reveal that employers learn the verbal and quantitative skills of high school and college graduates very differently. It appears that employers are not very interested in the verbal skills of college graduates. Instead, they care much more about the ability to work with numbers and mathematics. The greater emphasis on quantitative skills in the college market is not very surprising. Well-educated workers are usually employed in occupations that require strong mathematical ability, and they need to perform a significant amount of work with numerical data. The finding that employers almost perfectly learn the quantitative skills of college graduates at the time of initial hire are consistent with Arcidiacono, Bayer, and Hizmo (2010)'s notion of ability revelation in the college labor market. There is substantial evidence in the employer learning literature provides support for their argument. Arcidiacono, Bayer, and Hizmo (2010) explain that the rich information contained in resume of college graduates may contribute to ability revelation. Therefore, a possible explanation for the perfect revelation of quantitative skills in the college market is that highly-educated workers are capable of perfectly revealing their skills. However, it is also possible that employers make great efforts to accurately evaluate the quantitative skills of potential workers in the hiring process due to the importance of this type of skills.

In this section, we study the role of verbal and quantitative skills in wage determination and their corresponding employer learning processes for high school and college graduates, respectively, and report the following three interesting findings. First, verbal skills are relatively more important than quantitative skills for high school graduates. Second, quantitative ability is of particular importance to college graduates while the influence of their verbal skills is not significant. Third, employers almost directly learn verbal skills but gradually learn quantitative skills in the high school market, and in the college market, they pay very little attention to verbal skills and almost perfectly learn quantitative skills of their potential workers.

4.4 Conclusion

This chapter investigates how verbal and quantitative skills affect labor market earnings under the framework of employer learning and statistical discrimination. Though there is an extensive literature on employer learning devoted to general cognitive ability, specific types of skills such as verbal and quantitative skills are relatively under-researched. In this chapter, we focus on two basic types of cognitive skills, verbal and quantitative skills, and analyze the importance of these two skills in worker's wage determination.

Using the NLSY79 data, we find that both verbal and quantitative skills have a big impact on worker's wage but quantitative ability turns out to be a more important determinant of earnings. It is worth noting that, when workers enter the labor market, verbal skills are almost fully rewarded but quantitative skills are only partially rewarded. Interpreted through the perspective of employer learning, employer directly learn workers' verbal skills but gradually learn their quantitative skills. Furthermore, our analysis results suggest that the importance of verbal and quantitative skills varies with educational level. For high school graduates, there are large economic returns to both types of skills, and verbal skills are relatively more important than quantitative skills. On the contrary, quantitative skills play a crucial part in the earnings of college-educated workers while the impact of verbal skills is very small. The employer learning process of these two types of skills also differs between high school graduates and college graduates. For high school graduates, employers directly learn their verbal skills and some parts of their quantitative skills immediately upon entering the labor market, and gradually learn more about their quantitative skills during the employment period. In the case of college graduates, verbal skills are somewhat irrelevant, and employers are able to directly learn most parts of their quantitative skills.

In this chapter, we investigate the role of verbal and quantitative skills in the wage determination of the NLSY79 generation. The role of technology and science is increasing in today's knowledge economy, it is of interest to compare the levels and rates of influence of verbal and quantitative abilities on wages. Murnane, Willett, and Levy (1995) show that basic cognitive skills had a larger impact on wages for 24-year-old men and women in 1986 than in 1978, and conclude that these skills were becoming more important in wage determination on an economy-wide basis. One direction for future research is to examine how the relationships between verbal and quantitative skills and wage evolve over time. The analysis will provide an answer to some questions of interest. Are wages more dependent on worker's verbal and quantitative skills in an era of apparently rising demand for skills? Which type of skills are becoming more important in determining wages of young workers, verbal skills or quantitative skills? These research findings can be draw upon by policy markers to help design and evaluate learning programs that aim to improving the labor market outcomes of disadvantaged workers. Using the UK data, Vignoles, Coulon, and Marcenaro-Gutierrez (2011) undertake a cross cohort analysis and assess whether the wage return to literacy and numeracy skills have increased over time. Their results indicate that the labor market value of these two basic types of skills has remained noticeable stable over the time period 1995-2004,[10] implying that the increase in the supply of these skills since the early 1990s has been at least matched by the increase in demand in the UK labor market. Our analysis is a useful starting point for future discussion on the evolution of the returns to verbal and quantitative skills in the U.S. labor market.

Division of labor and specialization is one of the key features of modern economic systems, leading to a large increase in productivity. There exists a large number of job positions in today's economy, and different positions require a different mix of skills and experience. The requirements for a job vary according to the nature of the job itself, and job descriptions list what sorts of abilities a successful applicant should have. Consequently, the labor market value of different types of skills should vary with job positions. For example, interpersonal and communication skills are crucial for sales jobs, and engineering jobs usually require strong technical and quantitative backgrounds. If a worker with high verbal skills are employed in an occupation that does not use those skills, the economic return to those skills is lower than if that worker are in a job requiring excellent verbal skills. A fruitful avenue for future research is to analyze the role of different types of skills as well as the corresponding employer learning process for a variety of occupations.

[10]The return to literacy is very similar across two cohorts, one in 1995 and the other in 2004. The return to numeracy is somewhat decreased in the later cohort, but there is no significant differences between these two cohorts.

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