EMPLOYER LEARNING AND STATISTICAL DISCRIMINATION: A COMPARISON OF HISPANIC AND WHITE MALES

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1. Introduction

The Employer Learning with Statistical Discrimination (EL-SD) model, first proposed by Altonji and Pierret (AP) [2001], greatly contributes to the understanding on how information about workers' productivity is assimilated by employers through time. A worker's productivity at the start of his career is unknown by firms. Consequently, in order to valuate productivity and set wages, employers make a preliminary assessment of the workers based on his observable characteristics such as race, years of education, among others, which means they statistically discriminate on the basis of those directly observed traits. With time, employers are able to observe the worker's job performance and "learn" about his productivity, which makes initial information used to assess the worker's productivity redundant. Indeed, using the 1979 cohort of the National Longitudinal Survey of Youth (NSLY79) data from African American and white males entering the labor market, AP found that the estimated wage effect of education will fall as workers gain experience, while as firms learn about their productivity, the estimated effect of hard-to-observe correlates of productivity will rise. However, they found little evidence for statistical discrimination in wages on the basis of race.

It is a known empirical fact that young black males are more likely to be raised in poorer homes and neighborhoods, have less educated parents, and attend lower quality schools. Nonetheless, individuals of Hispanic identity are also exposed to similar life conditions growing up. Both Hispanic and black individuals scoring lower than their white peers in standardized cognitive tests is a robust indicator of the existent skill differential among them that has proven to have considerable power in explaining racial differences in wages. However, aside from sharing similar socioeconomic disadvantages with African Americans, some Hispanics have immigration status issues and a noticeable accent that could add as possible reasons to become targets for discrimination.

EL-SD literature that focuses on Hispanics is scarce. On the contrary, there are numerous studies that emphasize wage differentials between African American and white individuals. Past empirical exercises underscore the value of available statistical information about Hispanic males. Most of the employer learning literature has been devoted to the black-white earnings differential and, as a consequence, the economic understanding about EL-SD between Hispanics, an ever growing community in the United States, and the rest of the population is not studied in depth.

The present analysis is based on the male portion of NSLY79, which contains information for individuals that were 14 to 22 years old when they were first interviewed. This paper is intended to test if there is statistical discrimination in terms of wage against Hispanics with respect to whites when they enter the labor market and to observe how this situation changes as employers gather new productivity information about the worker.

This empirical exercise is based on the EL-SD model proposed by AP, where they evaluate earning differentials and employer learning profiles between African American and white male workers. I replicated AP's exercise for the non-Hispanic portion of the sample and then extended their original analysis to Hispanic individuals. Finally, a variation of AP's EL-SD model, proposed by Arcidiacono et al. [2010], allows me to assess how relevant is to hold a high school or college degree in the firm's evaluation of the worker at the moment of hire and its evolution through time, which will also be analyzed from the race/ethnicity perspective.

Farber and Gibbons (FG) [1996] greatly contributed to the understanding of how firms learn about the worker's productivity as he accumulates experience. The basic idea behind their employer learning model is that at the beginning of a worker's career employers are not able to directly see how productive the individual is, so they make a first evaluation with the information they have available at the moment of hire. In this initial period firms set a wage, which is equivalent to the worker's expected output conditional on his observable attributes. During the following periods, employers are capable of learning about the worker's real productivity as they observe each period's output and pay them accordingly. FG study the effect employer learning has on wage evolution through variables that they do not initially observe but that are increasingly correlated with productivity as the worker accumulates experience. Specifically, they isolate hard-to-observe variables from the components that employers may observe at market entry. Since the worker's productivity is learned by the employer as experience is gained, FG expect that the estimated wage effect of productivity and, hence, hard-to-observe variables purged from all directly observed traits, will rise with labor market experience.

Notwithstanding, limiting the effect of employer learning to what they do not observe when they first hire individuals excludes the possibility to test for statistical discrimination[1]. AP propose a way to do the latter based on the original FG model but using, however, the variables that employers directly observe to test if statistical discrimination is present at the moment of hire and how this initial assessment of the worker's productivity develops as the employer learns over time. In their paper, AP suggest that employers might statistically discriminate against workers on the basis of initially visible traits they believe are correlated with productivity because of the restricted amount of information they have available. Nonetheless, as individuals accumulate experience, employers should be able to observe the worker's performance, making initial information unnecessary over time.

In standard EL-SD literature, there are two types of variables that are correlated with productivity: easy-to-see *s* variables that are directly observed by firms (such as schooling), and hard-to-see *z* variables that are initially not observed or fully used by firms (like AFQT standardized scores). AP maintain that, if the *s* and *z* variables are positively correlated, EL-SD theory implies that the estimated wage effect of the *z* variable will be non-decreasing as the worker accumulates experience and the employer learns about his productivity, whereas the earnings effect of the *s* variable will be non-increasing, since it does not contribute to the firm with any new information about the worker's productivity. AP test if schooling and race are used by employers to statistically discriminate. In case employers use education as a signal of productivity, the model predicts that, although the initially estimated wage effect of an additional year of education should be large, it should not increase with experience. EL-SD also predicts that, if belonging to a particular race is statistically negatively associated with productivity, there should be an initial negative wage gap but as employers observe the worker's performance in each period, wages should depend more on actual productivity and less on race.

Arcidiacono et al. [2010] propose a variation of AP's model (the revelation of ability model) that seeks to explain how workers reveal their ability to firms through educational attainment. AFQT standardized scores in the NLSY79 are used as a proxy for ability, which they suggest has considerable power to predict a worker's productivity. They argue that a college degree is used by workers to reveal their initially not observed ability to employers. To

[1] Statistical discrimination takes place when distinctions between demographic groups are made on the basis of real or unreal statistical differences between these groups.

empirically prove this, they divide the sample in two groups (high school and college graduates) and perform AP´s econometric specification for each one of them instead of including years of education as a variable in the model. Their results show that ability is revealed almost completely for college graduates, whereas it is observed gradually for high school graduates. Arcidiacono et al. note that results obtained with their model suggest that pooling all levels of education could bias estimates and, consequently, AP's conclusions should be reviewed.

The EL-SD theory agrees that there can be other factors that might be causing the racial wage differential, either at market entry or as the individual accumulates experience. One example is Becker's taste-based discrimination[2]. Another is "social distance"[3] at higher level jobs, which means that, as experience is accumulated, this could be driving the increase in the wage gap between two racial/ethnic groups. For these reasons, AP advise to take their results of statistical discrimination in the basis of race with care. Similarly, Arcidiacono et al. state that there could be other reasons that may be driving the increasing race wage gap but that they are mainly aiming to test if this growing differential can be explained by EL-SD alone.

It is also worth noting that EL-SD empirical exercises in this document and those performed by AP and Arcidiacono et al. in their papers are about the wage differential among individuals and not about an unemployment gap. In fact, Ritter and Taylor [2011] showed that, even though the wage gap between African Americans and whites can be mostly explained by pre-market skill differentials (Neal and Johnson) [1996], this conclusion does not extend to the unemployment gap between these two groups. Moreover, according to Neal and Johnson, the Hispanic-white earnings gap is completely explained by differences in skills before labor market entry. Nonetheless, Ritter and Taylor also reported a substantial unemployment differential between Hispanics and whites, although smaller than that of blacks and whites, when controlling

[2] In Becker's (1957) taste-based discrimination model, there are discriminating employers that only hire members of a specific group. A wage differential appears in case the fraction of employers that discriminate is large enough that the demand for workers from the discriminated group is less than the supply when wages for both groups are equal. Then some of the workers that belong to the discriminated group have to work for discriminating employers for lower wages in the short run. In a competitive market, since each worker earns the marginal product he generates, discriminating employers must pay for their distaste themselves, allowing the equilibrium wage to reappear in the long run. However, if there is taste-based discrimination by customers, then competitive markets will not punish discriminating employers.

[3] Yancer (2003) explains that higher levels of social distance measures mean that people will attempt to distance themselves from members of another race and will likely seek out ways to exclude them from their lives. On the contrary, lower levels of social distance make it easier for a minority group to eventually become accepted into the dominant culture.

for pre-market acquired skills. As a result, for both African Americans and Hispanics, there is a large unexplained unemployment gap with respect to their similar white peers.

The main predictions of the EL-SD model still hold in my replication of AP's empirical exercise for the non-Hispanic sample, where estimates are very similar both in direction of effects and statistical significance. I thus assume this replication exercise is closely accomplished. Furthermore, results obtained from the comparison of Hispanic and white individuals indicate that there is little evidence of statistical discrimination against Hispanics in terms of wages; however, that based on years of education is still present.

In my replication of the revelation of ability model, with a slightly different sample from that proposed by Arcidiacono et al., results seem to follow their revelation of ability predictions for the high school sample: ability is not directly observed in the wage setting process at labor market entry but gradually revealed as workers accumulate experience, which is an implication similar to that proposed in AP´s EL-SD model. On the other hand, Arcidiacono et al. believe that a college diploma communicates ability to the labor market in a discrete lump, rather than gradually as in the high school market. Nonetheless, ability seems to be partly revealed at market entry and continues to be revealed as the worker gains experience, which is not what the revelation of ability theory predicts. Moreover, I did not find conclusive evidence of employers statistically discriminating in the basis of Hispanic identity in terms of wages, not in the high school nor the college labor markets.

The paper begins with a summary of the EL-SD model and its revelation of ability variation, which make up for the theoretical framework of this analysis, and a review of their main empirical implications. I next describe the data and the econometric specifications used in this exercise. Afterwards, I report detailed results and elaborate on how these collide with the main EL-SD and revelation of ability hypotheses. In the final section I close this paper with the conclusions of this exercise.

2. A review of the EL-SD model

In this section, I will summarize basic theoretical assumptions and empirical implications of the EL-SD model developed by AP [2001], and its variation proposed by Arcidiacono et al. [2010]

2.1. Basic theoretical assumptions of the EL-SD model

2.1.1. Summary of Altonji and Pierret [2001]

AP proposes an equation to express the worker's labor market productivity for worker *i* with t_i years of experience:

$$y_{it} = rs_i + \Lambda z_i + \alpha_1 q_i + +\eta_i + H(t_i)$$

where y_{it} is the log of labor market productivity, which is composed by four different types of variables. First, there are easy-to-see *s* variables that are correlates of productivity (such as schooling) and which can be observed and used by both employers and researchers. Second, there are hard-to-see *z* variables correlated with productivity in a way that is not directly observed by employers but readily observed by researchers (like standardized AFQT scores, oldest sibling's wage and father's education). Third, there are *q* variables that are observed by employers but not by researchers (i.e. direct observation) and, fourth, there is an index η that makes up for determinants of productivity that are not directly seen by employers and unknown or not used by the econometricians. In addition, $H(t_i)$ is the experience profile of productivity[4].

The theoretical framework used by AP offers two views of the same problem. On the one hand, there is the employer's point of view and, on the other hand, there is that of the researcher. From the employer perspective, the worker's productivity at the moment of hire is assessed based on what he observes (*q* and *s*). There are other parts of labor market productivity that employers do not observe (*z* and η). Nevertheless, employers formulate conditional expectations of the latter using the information they have available. At any given period of time, the employer needs to assess the worker´s expected productivity in order to decide on the wage he is going to receive. As the worker gains experience, employers are able to see his job performance D_{it} in each period of time and update their valuation of his productivity. Consequently, the wage paid

[4] AP assume that $H(t_i)$ does not depend on s_i, z_i, q_i, or η_i .

to the worker is the expectation that firms have of his productivity at any given moment, which will change as he accumulates experience.

The other perspective of a worker's productivity is that of the researcher, who is able to observe *s* and *z*¸ but not *q* and η. Although the researcher cannot observe D_{it}, he does observe his wage in each period, which AP assume is the expectation that firms have of his productivity, conditional on what it is observed (s_i, q_i and D_{it}) by employers. As a consequence, the log of wage is given according to the following formula:

$$\ln(W_{it}) = (r + \Lambda\gamma_2 + \alpha_2)s_i + H^*(t_i) + (\alpha_1 + \Lambda\gamma_1)q_i + E(\Lambda v_i + e_i \mid D_{it}) + \xi_{it} \qquad (2)$$

where $(r+\Lambda\gamma_2+\alpha_2)$ is the coefficient on the easy-to-see *s* variable, which could be education, race/ethnicity, among others; $(\alpha_1+\Lambda\gamma_1)$ is the coefficient on the *q* variable, which could be the employer's direct observation of the worker; $H^*(t_i)$ is the experience profile of productivity and it is expressed as $H^*(t_i) = H(t_i) + \log(E(\exp^{\mu_{it}}))$[5]. The $E(\Lambda v_i + e_i \mid D_{it})$ term is the expected value of the error term of the worker's log of productivity at labor market entry conditional on his performance in each period, which means that, based on D_{it}, employers can change their initial valuation of the worker's productivity.

The researcher cannot see either *q* or $E(\Lambda v_i + e_i \mid D_{it})$, so in order to model the log of wages (see equation 2), according to the omitted variable bias formula the coefficients on *s* and *z* will be equal to:

$$b_{st} = b_{s0} + \Phi_{st} = [r + \Lambda\gamma_2 + \alpha_2] + \Phi_{qs} + \Phi_{st} \qquad (3)$$

$$b_{zt} = b_{z0} + \Phi_{zt} = \Phi_{qz} + \Phi_{zt} \qquad (4)$$

where Φ_{qs} and Φ_{qz} are the coefficients of the regression $(\alpha_1+\Lambda\gamma_1)q_i$ on s_i and z_i; and Φ_{st} and Φ_{zt} are the coefficients of the regression of $E(\Lambda v_i + e_i \mid D_{it})$ on s_i and z_i. This means that

[5] In Mathematical Appendix I.a., I show the main assumptions behind this formula and how it is obtained.

the effect of s is going to be determined by its initial effect ($[r+\Lambda\gamma_2+\alpha_2]+\Phi_{qs}$) and its experience effect Φ_{st}. Similarly, the effect of z will be determined by its initial and experience effects (Φ_{qz} and Φ_{zt}, respectively).

Based on the model presented above and assuming s and z are positively correlated, AP make two propositions. First they propose that, under the assumptions of the above model, the effect of the easy-to-see s variable b_{st} on the log of wages is "non-increasing" with experience and the effect of hard-to-see z variables b_{zt} is "non-decreasing" with experience. This means that variables that employers initially observe will get the credit for those they do not observe directly, (z like AFQT scores, sibling's wage, and father's years of education), unless the latter are included in the wage equation and interacted with experience. It is precisely because the effect of employer learning on z spreads to s that AP are able to test statistical discrimination. The second proposition states that: $\frac{\partial b_{st}}{\partial t}=-\Phi_{zs}\frac{\partial b_{zt}}{\partial t}$, where $-\Phi_{zs}$ is the coefficient in the regression of z on s. This last formula means that the decrease in b_{st} as the worker accumulates experience will be equal to the change in b_{zt} over time, weighted by the association between z and s.

2.1.2. Summary of Arcidiacono et al. [2010]

Arcidiacono et al. propose a model which is a variation of AP´s original EL-SD model (for a complete description, see the Mathematical Appendix I.b.). The main idea behind the revelation of ability model is that ability of high school graduates is not initially observed by firms but it is continuously shown as they accumulate experience. Conversely, a college diploma might reveal ability in a discrete lump at market entry but do not offer more ability information over time. To empirically test this assumption, Arcidiacono et al. divide the sample into high school and college graduates. Ability is assumed to be correlated with productivity in a way that is not directly seen by employers and, as a result, not a determinant of wages when the worker is first hired. Arcidiacono et al. use standardized AFQT scores as a proxy for ability, which is a similar concept to AP's hard-to-see z variable.

Arcidiacono et al. also assume that the worker´s labor market productivity is a function of an easy-to-see s variable, direct observation q, a hard-to-see z variable, productivity information not observed by the employer nor the econometrician η_i , and an experience profile $\tilde{H}(t_i)$. As in AP´s model, Arcidiacono et al. assume that worker´s earnings are equivalent to their expected productivity.

Comparable to AP, the revelation of ability model offers two perspectives over which labor market productivity is observed, that of the employer and that of the researcher. However, unlike AP, Arcidiacono et al. assumes that the employer is able to observe the mean ability (z) of the race the worker belongs to. At market entry, the employer knows nothing about the worker´s actual ability, which means that they predict the worker´s productivity based on easy-to-see *s* variables, the race average ability z and direct observation *q*. On the following periods, employers update their initial beliefs about the worker with new information about ability. As long as employers learn about the worker´s actual ability, the group average ability will become redundant.

There are two main differences between Arcidiacono et al. and AP's employer learning with statistical discrimination models. First, as mentioned above, Arcidiacono et al. believe that education is not only an indicator used by firms to assess a workers' productivity but it is a way for workers to reveal their ability to firms. They think that ability in the high school graduate labor market is not observed, so employers gradually learn about the worker´s productivity as he gains experience. However, they believe that ability is nearly perfectly revealed to employers because a college diploma communicates ability information in a discrete lump at market entry. To test this hypothesis, they perform AP's econometric specification for two separate groups: the college and the high school samples. Arcidiacono et al. note that, if their revelation of ability hypothesis is true, pooling all levels of education would result in biased wage effects.

The second difference is that Arcidiacono et al. argue they found statistical discrimination on the basis of race for the high school sample. In the standard EL-SD model, the latter would imply that race is an *s* variable that is treated by the employer as relevant information at the wage setting process at labor market entry. Arcidiacono et al. proposes a different theoretical scheme to address racial effects on wages. As described above, they assume that average racial group ability is known by employers and that one of the groups has a lower average ability. As ability does not have a wage effect at market entry, since it is not observed, discriminating employers will put all weight in the worker's average productivity and, consequently, have even more incentives to discriminate. Consequently, the initial racial prejudgment will dominate the overall wage effect over time, although the learning effect starts to appear as experience is accumulated and will tend to decrease it.

2.2. Empirical implications of the EL-SD model

2.2.1. EL-SD on the basis of education

In this section the empirical implications of using education as an easy-to-see *s* variable will be reviewed. Hard-to-see *z* variables used in this exercise such as AFQT scores, sibling's wage and father's education are positively correlated with education.

If a firm statistically discriminates on the basis of education, it is going to use it in order to predict the productivity of a new worker. However, as the worker accumulates experience and his performance is observed, his real productivity will be gradually revealed to the employer. This way the worker's wage will be more dependent on new information about productivity and less dependent on the initial characteristics when he was first hired.

Under the assumptions of the model described in section 2.1.1., if employers statistically discriminate on the basis of education at the beginning of the worker's career but learn about his productivity as they observe his job performance in each period of time, results will conform to the following proposition:

The EL-SD model predicts that the estimated impact of an s variable is non-increasing with experience and that the estimated impact of a z variable is non-decreasing with experience, provided z x t is included in the regression.

AP succinctly explain the intuition behind this hypothesis: "as employers learn the productivity of workers, *s* [education] will get less credit for an association with productivity that arises because *s* is correlated with *z*, provided that *z* is included in the wage equation with a time-dependent coefficient and can claim credit." In the case of *z*, if employers do not initially observe a worker's productivity but are able to learn about it in each period, the effect of a *z* variable at market entry will exclusively depend on its correlation with *q* (see equation 3) but the proposition above predicts, nonetheless, that the overall effect of *z* should increase over time.

Statistical discrimination on the basis of education is easily related to the revelation of ability model proposed by Arcidiacono et al. In the high school labor market, ability is not directly observed by employers but gradually revealed through their job performance as they accumulate experience. In that sense, the estimated impact of a *z* variable in the high school sample should conform to the earlier mentioned proposition that predicts it will be non-decreasing with experience.

Conversely, Arcidiacono et al. propose that college graduates are disclosing most of their ability in a discrete lump, rather than continuously through time. Thus, the estimated wage effect of a *z* variable for the college labor market should be opposed to that obtained for the high school sample. The coefficient on the *z* variable will be non-increasing as the worker accumulates experience: returns to AFQT scores should be large at the beginning of the worker's career and should not change with experience.

2.2.2. EL-SD on the basis of ethnicity

In their paper, AP examine the possibility that there is statistical discrimination and employer learning towards African Americans when compared to white individuals. The main objective of this paper is to evaluate if their EL-SD model predictions about race can be extended to individuals of Hispanic ethnicity when compared with white non-Hispanic individuals.

There are easy-to-see *s* variables (observed and used by both employers and researchers) and there are hard-to-see *z* variables (correlated with productivity not observed by employers but observed by researchers).

AP note that in the model they are proposing, race/ethnicity can either act as an *s* or a *z* variable. If employers statistically discriminate in the basis of race/ethnicity, this would imply that race is an *s* variable. In this case, a negative correlation between a specific racial/ethnic group and productivity is assumed by employers at market entry and, as a result, an earnings differential between the discriminated and preferred races (or ethnicities) is generated. However, as the employer observes signals of the worker´s productivity through his job performance, the wage setting process will be less based on the employer´s initial belief about that race/ethnicity association with productivity and more on new information about productivity. Consequently, the model predicts that the initial estimated effect of race/ethnicity will be negative but it will increase toward zero as the worker accumulates experience.

There is also the possibility that race will have the properties of a *z* variable, which would happen if employers could statistically discriminate in the basis of race/ethnicity but choose not to when assessing a worker's productivity. Consequently, the model predicts that at the beginning of the worker´s career, if the employer ignores race/ethnicity, its initial estimated effect should be smaller than if the employer would fully use it to statistically discriminate. This means that there should not be any other initial effect insofar as that originated by the correlation of z with q variables (see equation 4). Furthermore, as the individual accumulates experience, employers would observe their performance over time and would pay them accordingly. As a result, the effect of race/ethnicity interacted with experience should decrease. According to AP, the intuition behind this is that, although firms are obeying the law by not using race/ethnicity information as a cheap indicator of productivity at market entry, they may be acquiring more knowledge about productivity over time that may be "legitimately used to differentiate wages among workers".

Consequently, under the assumptions of the above described model, the EL-SD model implies the following propositions:

If employers statistically discriminate on the basis of ethnicity, it is an s variable and its estimated impact gets closer to zero as the worker gains experience over time. For an ethnicity with lower average productivity, its estimated effect is negative and increases toward zero with experience, provided z x t is included in the regression.

If employers do not statistically discriminate on the basis of ethnicity, it acts like a z variable. For an ethnicity with lower average productivity, the estimated ethnicity effect is smaller than if firms illegally use race as information and decreases with experience, provided s x t is included in the regression[6].

Statistical discrimination on the basis of race/ethnicity can somewhat relate to the revelation of ability model proposed by Arcidiacono et al. They claim they found statistical discrimination in the basis of race for their high school non-Hispanic sample, which in the standard EL-SD model would imply race/ethnicity is considered an easy-to-see s variable that is treated by the employer as relevant information at the wage setting process. For a race or ethnicity with lower average productivity, the above described proposition predicts that the estimated effect is negative but it will increase toward zero with experience.

[6] The effect of a z variable at market entry will exclusively depend on its correlation with q (see equation 4 in subection 2.1.1.).

Nonetheless, Arcidiacono et al. propose a different theoretical model that they argue reconciles a growing negative wage gap with experience for the high school sample with the EL-SD model predictions about race/ethnicity. Arcidiacono et al. maintain statistical discrimination in this scenario is still possible if returns to ability increase with experience. The rationale behind this is that ability, which is not directly observed by employers, will not be a determinant of wages at the beginning of the worker's career. Although ability should grow in importance as the individual's performance is observed in each period of time, when a person of a particular race/ethnicity associated with lower levels of productivity enters the labor market, discriminating employers put more weight on his average group productivity. Consequently, the initial racial prejudgment will dominate the overall wage effect, although the learning effect starts to appear as experience is accumulated and will tend to decrease it.

3. Data and Econometric Specification

In this section, a complete description of the data is offered, the empirical method is identified and econometric model is specified.

3.1. Data description and variable construction

NLSY79 data set is a nationally representative sample of 12,686 respondents born between 1956 and 1965. The dataset contain comprehensive information for the first survey in 1979 and follow-up surveys for over thirty years. Individuals included in the sample were surveyed in a yearly basis from 1979 to 1994, and biennially from 1996 to 2010. Altonji and Pierret [2001] worked exclusively with a group of 5,403 non-Hispanic males from 1979 to 1992. Nonetheless, including Hispanic males, there are 6403 male respondents in the NLSY79.

I followed AP's sample construction steps as closely as possible. They consider work experience valid only after the individual has left school for the first time. AP defined potential experience as age minus years of education minus six. Furthermore, the actual experience measure reports the number of weeks in which respondents have reported working at least 30 hours a week since they first left school. If respondents ever return to school, weeks of experience are still included in the actual experience variable if they comply with the 30 hours-per-week rule. The sample is restricted to individuals who accumulated any experience in civilian jobs. If an individual reported to be in active military service, he is assumed not to be employed for the time his military duty lasts but he remains in the sample. After the actual experience variable in weeks is computed, it is divided by 50 so it can be expressed in years.

In order to calculate actual experience, first it is necessary to compute the date in which respondents were last enrolled in school. The date in which they first reported working hours after leaving school is the start work week. To find the first week in which the individual reported positive worked hours and, consequently, their first reported job, the NLSY "hours-at-all-jobs" weekly variable array is used. Interviews do not always take place every year but that does not mean an individual must be dropped from the sample. When an interview takes place, all work experience information since the last interview is collected, which is why all dates of all interviews are computed. The measure of actual experience is the cumulative sum of the number of weeks worked from the start work week to the first interview plus the number of weeks worked between interviews. Only weeks that comply with the 30 hours-per-week rule are included.

However, it is necessary to mention that a sizable section of the survey (around 28% of the male sample) was last enrolled in school before 1978. Information before this year is not as comprehensive as that recorded in the following years. Consequently, AP limit their sample to individuals for whom it was possible to reconstruct their work history. Since the NLSY79's "hours-at-all-jobs" weekly array only go back to the first week of 1978, it was necessary to reconstruct their work history before that date.

In order to accurately account for all work weeks after individuals were last enrolled in school or held their first job (whichever occurred last), I created weekly variables from 1973 to 1977 and I filled them in with weekly work information about each individual. In the year 1979 respondents were asked if they actively participated in the armed forces before that year, in which case beginning and stopping dates were recorded. As stated before, any military spells are considered as periods in which respondents were not employed. Moreover, those who were last enrolled in school before 1978 were asked if they have had held a job after leaving school, and beginning and stopping dates if that was the case. If I could not account for a worker's labor status after first leaving school for more than 5 weeks (which means that it is not possible to assess if the person was working, unemployed, or in the military), the individual is dropped from the sample.

For respondents who were last enrolled before 1978 and for whom a complete work history was reconstructed, experience variables are computed in a similar way as those who were last enrolled after 1978. The measure of actual experience for this section of the sample is simply the cumulative sum of the number of 30-hour-weeks worked from the start work week to the last week of 1977, the number of 30-hour-weeks worked from the first week of 1978 to the first interview and weeks worked between interviews until the last interview in which they participated.

Labor information other than the calculation of the experience variables is restricted to the analysis of the current employer (CPS job[7]) and it is used only for years in which the respondent was working at the job in the moment of the interview. The wage variable is the hourly rate of pay at current job. Considering there are multiple wage observations for each individual corresponding to years from 1979 to 1992, these were divided by the fixed-weighted price index for GDP personal consumption expenditure with 1987 as base year to obtain wages[8] converted to 1987 dollars. Observations where individuals reported to have real wages less than $2 or more than $100 dollars were set to missing values.

The education variable, or easy-to-see *s* variable, is the highest grade completed by the respondent at the time of each interview, which implies that the level of education reported at the first interview is considered to be correct and that years of education are either constant or increasing through time. Furthermore, respondents who had not completed at least 8 years of education until 1992 are dropped from the sample.

The Armed Forces Qualifications Test (AFQT) scores are used by AP as a correlate of productivity and hard-to-see *z* variable. It is worth mentioning that AFQT scores that appear in the survey are computed as the sum of certain sections of the Armed Services Vocational Aptitude Battery (ASVAB)[9]. ASVAB scores are available for 94% of respondents in the NLSY79. These tests were taken by NSLY79 participants during the summer and fall of 1980. At the moment of taking the test, respondents were asked about their dates of birth and some of them presented discrepancies with respect to the dates of birth reported in 1979 at the first interview[10]. Neal and Johnson [2006] noted that the AFQT test is a test of acquired skills and not

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[7] The CPS employer is the current or most recent job held by the respondent at the time of the interview. This type of job is the more closely followed by the NLSY79. If the person in question was working at more than one job, the CPS job will be that in which the respondent worked the greatest number of hours; if the respondent has two jobs in which he/she works for the same amount of hours, the CPS job will be the one in which the respondent has worked the longest.

[8] U.S. Department of Commerce, "*Statistical Abstract of the United States 1993*", p. 493.

[9] Altonji and Pierret [2001] use the 1989 definition of the AFQT test. Since January 1989, the Department of Defense changed the definition of measure of AFQT scores. This revised version of AFQT scores is the sum of three scaled scores: arithmetic reasoning, math knowledge and twice the verbal composite. The latter is computed as the scaled version of the sum of two sections: word knowledge and paragraph comprehension scores. As noted by (Blackburn 2004), both scaled scores have the same standard deviation, so the fact that the verbal composite is multiplied by two results in an equal weighting of the verbal and mathematical sections of the AFQT.

[10] In the following empirical analysis, dates of birth that are considered correct are those reported in 1980 by individuals at the ASVAB test locations, and for those who chose not to take the exam or were not interviewed that year, date of birth is that reported in the 1979 interview. To account for the fact that age at which respondents took the test is not the same for all participants, the AFQT scores are standardized by age at the time of the test using

of innate ability, which means that when looking at AFQT scores, we focus on the skill differential between races or ethnic groups that is learned over time.

Altonji and Pierret worry about the type of job an individual would hold at the beginning of his career because workers with higher levels of education would typically be hired for high paying jobs[11]. In order to control for the kind of job the respondent initially held, there is a variable in the NLSY79 that records occupational codes[12] for all jobs. After identifying the year in which the respondent held his first civilian job (occupation at which the individual first reported positive hours of work) and the corresponding first job occupational code, a group of dichotomous variables (one for each two-digit occupation code) was created.

AP also consider siblings' wages and father's years of education as correlates of productivity and hard-to-see *z* variables. In order to construct the former, the wage of the oldest sibling available in the NLSY79 sample (male or female) is recorded[13]. The wage that is taken for this analysis is the average hourly wage between the fifth and eight year after the sibling has left formal schooling for the first time. If the variable that indicates father's education is below four years, it is set to 4.

Out of the 6,403 individuals in the non-Hispanic sample, I dropped 448 who report having left school until 1992 or do not have a date for the first time they left school. I also dropped 921 individuals who were last enrolled in school before 1978 and for whom work history could not be constructed. From the 5,034 remaining respondents, 61 were dropped because they did not complete at least 8 years of schooling. Also, 399 individuals had missing wages and 128 did not report AFQT scores, 1091 did not have a valid code for first job occupation and for 4 individuals urban or rural status was missing. Out the 2,860 individuals that remained in the sample, 491 were Hispanics, 851 were African American and 2009 were whites. In Table 1 the number of individuals and the reasons to be dropped from the sample are presented.

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sample weights. In order to do the latter, ASVAB sample weights provided by the Bureau of Labor Statistics were used. Afterwards, the mean score for each age is subtracted and then divided by the standard deviation for each age.

[11] AP state that one possible objection to theoretical framework model is that it assumes that employer learning is independent of the type of job in which the worker begins his career, which is why they include controls for the two-digits occupation of the first job.

[12] The 3-digit 1970 Census classifications (U.S. Census Bureau 1971): http://www.nlsinfo.org/nlsy79/docs/79html/79text/occupat.htm

[13] The regression includes dichotomous variables for individuals who did not know their father, for whom ASVAB scores and/or siblings wages were not available, and for those who have female siblings.

Table 1

NLSY79 Male Sample						
	Hispanic	Black	White	Black-White	Hispanic-White	Total
Total Male	1,000	1,613	3,790	5,403	4,790	6,403
Not enrolled	906	1,470	3,579	5,049	4,485	5,955
Have valid work history	748	1,272	3,014	4,286	3,762	5,034
Have 8 years of education	729	1,264	2,980	4,244	3,709	4,973
Have valid jobs | wages	686	1,150	2,738	3,888	3,424	4,574
Have 1rst occupation	510	879	2,094	2,973	2,604	3,483
Have valid afqt score	491	851	2,013	2,864	2,504	3,355
Have valid urban obs	491	851	2,009	2,860	2,500	3,351

The following table shows some descriptive statistics of the complete male respondents.

Table 2

Descriptive Statistics Male Sample (N=3,351)				
Variable	Mean	St. Dev	Minimum	Maximum
Real hourly wage	8.52	5.00	2.00	96.46
Log of real hourly wage	2.02	0.49	0.69	4.57
Potential experience (yrs)	6.82	3.44	0.00	21.00
Actual experience (yrs)	4.53	3.20	0.00	18.24
Education (yrs)	13.14	2.32	8.00	20.00
Black dummy	0.24	0.43	0.00	1.00
Hispanic dummy	0.16	0.37	0.00	1.00
Standarized AFQT Score	-0.05	1.04	-3.05	1.92
Do not know sibling's wage	0.51	0.50	0.00	1.00
Log of sibling's wage	1.98	0.46	0.70	3.78
Do not know father's education	0.12	0.32	0.00	1.00
Father's education (yrs)	11.62	0.34	4.00	20.00

Arciciacono et al. also follow AP’s data construction steps closely. Nonetheless, they divide the sample in two groups: high school and college graduates. They assume that individuals that have 12 and 16 years of education are high school and college graduates, respectively. Using the Current Population Survey, Jaeger and Page (1996) found considerable sheepskin effects to having high school and college degrees, as opposed to completing 12 or 16 years of education. The NLSY79 has a variable that indicates if a person has obtained a degree, aside from the information of years of education per individual. I created two variables that would indicate having a high school and college degree, one based on years of education and the other on having actually received a diploma.

Among other steps that Arcidiacono et al. took that were different from those taken by AP, they do not control for occupation at first job nor include time trend interactions. They also computed potential experience slightly different. Instead of subtracting age minus years of education minus six, they consider potential experience any years after the person first left formal schooling. If a person completes more years of education after entering the labor market, these are subtracted from the potential experience variable.

In addition, Arcidiacono et al. use the first 13 years of potential experience from 1979 to 2004. The data set I used is the same as the one used by AP in their 2001 exercise making all changes Aricidiacono et al. make, which are described above, but using data from 1979 to 1992. They also considered actual experience from all types of jobs held by respondents, while this exercise´s data set only considers experience from jobs in which 30 or more hours were worked.

3.2. Empirical method

I will test if there is statistical discrimination against Hispanics with respect to whites at the beginning of their careers and measure how this situation evolves over time, as the employer learns about the worker's productivity. In order to empirically observe this, the main objective is to test if EL-SD propositions, first applied to African Americans and whites, hold when Hispanics are compared to whites.

Another interesting question is how individuals' level of education communicates productivity to firms. Emulating Arcidiacono et al. econometric specification with a data set constructed as similar as possible to AP allows inferring if their revelation of ability theory is robust with a slightly different data set to that constructed by the authors. Performing this exercise will show if the inclusion of Hispanics changes Arcidiacono et al. main findings.

3.3. Econometric specification

The preferred econometric specification suggested by AP is the following:

$$\log(w_{it}) = \beta_o + \beta_{edu} edu_i + \beta_{AFQT} AFQT_i + \beta_r race_i + \beta_{edu,t} edu_i * t_i + \beta_{AFQT,t} AFQT_i * t_i \\ + \beta_{r,t} race_i * t_i + \beta_\phi \phi_i + f(t_i) + \varepsilon_{it}$$

where *edu* is years of education of the individual (*s* variable), AFQT represent standardized AFQT scores (*z* variable), t_i are cumulative years of experience, $f(t_i)$ is the experience function, ϕ_i other demographic controls and, finally, race (which could be an *s* variable if it is initially observed and used to statistically discriminate or a *z* variable if, although it is directly observed by the employer, it is not used in the wage setting process at the beginning of the worker's career). Besides standardized AFQT scores, the log of the oldest available sibling's wage and father's years of education are also later used as hard-to-see *z* variables. These variables are interacted with the cumulative experience variable as well in order to see how their estimated coefficients change as experience grows.

It is likely that higher levels of education are more valued for high paying jobs and, consequently, individuals with these qualifications would typically have access to these types of jobs at the start of their career. AP thought it would be important to include dummy variables for each occupational category at the job in which a person starts his or her career to control for this market entry characteristic.

In addition, because of the possibility of changes in the structure of wages in the United States during the time period of analysis, AP worry that estimators of the effect of experience and the other variables on wages might be misleading. They decide to control for year effects and to interact easy-to-see *s* and hard-to-see *z* variables with time trends, modeled as cubic polynomials. AP normalized their time trend interaction terms so that effects in the following tables refer to 1992 for a person with zero years of experience.

Using potential experience as the experience measure could bias the estimated effects on wages because potential and actual experience measures are not necessarily the same for all respondents. Since actual experience does not contain periods in which the individual is unemployed, out of the labor force or in military service, it better reflects the real time respondents were working in the labor market. However, including actual experience in the regression specification is not the correct approach. As affirmed by AP, actual experience is a labor "outcome" measure on its own right because it might be communicating a worker's labor market qualification to the employer. Consequently, AP decided to treat actual experience as an endogenous variable and use potential experience as an instrument. In fact, they consider any term involving actual experience (interactions with *s* or *z* variables, and each of the terms in which experience is expressed as a cubic polynomial) as endogenous and use its corresponding equivalent in potential experience as instruments.

Arcidiacono et al. basic econometric specification is very similar to that proposed by AP. The main difference is that they divided the male non-Hispanic sample into two groups: high school and college graduates, and estimated the same econometric specification for each group. In addition, they did not control for occupation at first job, used a slightly different potential experience measure[14], and did not controlled for time trend interactions. Jaeger and Page's sheepskin effect analysis (1996) showed significant wage effects to obtaining a degree as opposed to just complying with number of years required to graduate. In this paper I will test if results change when using actual degree reception instead of just using completed 12 or 16 years of education.

[14] Instead of subtracting age minus years of education minus six like AP did, they suggest that potential experience measure is the number of years since the respondent left school for the first time. Any additional year of education completed by the individual will be subtracted from the potential experience variable.

4. Results

First, a replication subsection is presented, in which similarities and differences of the replications exercises of this study are exposed. In the second and third subsections, education and ethnicity estimated effects on wages are detailed, respectively

4.1. Replications of AP [2001] and Arcidiacono et al. [2010]

4.1.1. Replication of Altonji and Pierret [2001]

I have performed a replication of AP´s EL-SD exercise, which results are shown in Appendix II (Tables 10-13). Their sample size has 21,058 observations accounting for 2,976 individuals, whereas mine has 18,407 observations and 2,761 individuals.

Similar to results obtained by AP, estimates in this replication exercise also showed that employers statistically discriminate on the basis of education. The coefficient on the education variable is large and statistically significant when the worker first enters the labor market, while its cumulative change after ten years is near zero and imprecisely estimated. On the other hand, returns to AFQT scores are small at market entry but as the employer learns about the worker's productivity, its cumulative effect becomes large and significant after ten years of experience. The racial earnings differential is small and negative initially and, as productivity is gradually observed, it widens. However, these racial effects are not statistically significant, not at the beginning of the workers career nor ten years later. AP use these results as evidence that there is not statistical discrimination in the basis of race. The estimated coefficients I obtained in all specifications performed by AP for the non-Hispanic sample are close to those reached by them in magnitude, direction of effects, and statistical significance. Even though there are minor differences, the main AP results still hold in this replication exercise.

I also replicated this econometric specification for all male individual (African Americans, Hispanics and whites) and found no significant differences in results with those reached in AP paper (see results at the end of Appendix II).

4.1.2. Replication of Arcidiacono, Hizmo and Bayer [2001]

I intended to replicate Arcidiacono et al. econometric specification following, however, the steps that AP used in the construction of their data set. It is important to mention that in the regressions performed by Arcidiacono et al. their high school sample size has 11,795 observations for individuals who have completed 12 years of education while this replication sample has 11,965 observations. Moreover, there are 9,301 observations for high school degree recipients. Similarly, the college sample used by Arcidiacono et al. has 4,112 observations for individuals with 16 years of education while this replication sample has 3,468 observations. Furthermore, there are 2,850 for college degree recipients.

Arcidiacono et al. state that ability, which they assume is highly correlated with productivity, is initially not observed but gradually revealed for high school graduates. Similar to results reached by Arcidiacono et al. in the high school sample, in this replication exercise the effect of standardized AFQT scores on the log of wages is small and statistically insignificant at the beginning of the worker's career but increases considerably with experience. This follows for both individuals with 12 years of education and with a high school degree. Consequently, these results support the hypothesis that ability is revealed with experience in the high school labor market.

The replication exercise reaches partially different results (see Table 3) in the matter of race in comparison to those obtained by Arcidiacono et al., although both datasets are constructed in a very similar way. According to the revelation of ability model, firms are expected to have strong incentives to statistically discriminate on the basis of race in the high school portion of the sample, since ability is not directly observed and belonging to a certain race is correlated with a lower group average ability. Arcidiacono et al. reached a negative and statistically significant initial effect on race. Similarly, it is negative and imprecisely estimated in this replication exercise. These results agree with the EL-SD hypothesis on race that there is statistical discrimination at market entry.

According to the revelation of ability model, as the employer learns about the individual's productivity, a widening racial wage gap over time is possible, although the learning effect will tend to decrease it. Arcidiacono et al. obtained a negative, although not statistically different from zero, cumulative change of the total effect of race, whereas in this exercise this effect is more negative and significant. It is also worth noting that the chosen definition of high school graduate does not seem to greatly affect estimated coefficients.

Table 3

Effects of Standardized AFQT Scores on Log Wages for High School Graduates - Non Hispanic sample

Model	ABH High School		Replication High School Sample			
	(1)		(2)		(3)	
Standardized AFQT	.008		.012		.011	
	(.013)		(.013)		(.015)	
Standardized AFQT *experience/10	.118	**	.105	**	.099	**
	(.017)		(.020)		(.023)	
Black	-.048	*	-.039		-.055	
	(.026)		(.027)		(.031)	
Black* experience/10	-.034		-.097	*	-.092	*
	(.035)		(.038)		(.043)	
R^2	0.187		0.159		0.173	
N observations	11,795		11,965		9,301	

All specifications control for urban residence, region, a cubic in experience, and year effects. Specification in column (1) presents estimates reached by Arcidiacono's et al. for individuals that had 12 years of education when they first left school. Specification in columns (2) and (3) presents estimates reached in this replication exercise. In column (2) results for individuals that had 12 years of education and in column (3) estimates for high school graduates that reported obtaining a degree are reported. Robust standard errors adjusted in the individual level.
* significant at the 5% level, **significant at the 1% level

In the college sample, Arcidiacono et al. argue that graduates almost perfectly reveal their ability to employers as they first enter the labor market. If this is true, the initial effect of AFQT scores on wages should be large. On the other hand, its experience profile effect should not vary over time because most of their ability is already "observed" by firms in period one.

For individuals who completed 16 years (see Table 4, specification 2), both the initial effect of AFQT scores and its experience profile effect are large and statistically significant. Conversely, degree awarded respondents report a large and statistically significant initial effect to AFQT scores while its interaction with experience effect is also great in magnitude but imprecisely estimated. These results show that ability is not only observed at labor market entry but also learned and valued by employers over time, which contradicts ABH's empirical prediction about ability revelation in the college market.

In the matter of race, African Americans show a wage premium with respect to whites in the college market. In order to explain this, it is worth noting that the unconditional mean of real wages of African Americans is similar to that of whites at market entry, although they score lower in the AFQT test[15], which is a robust fact of the US labor market. Using data from the CPS and the Census, Neal [2006] found that college educated African American and white males have similar wages upon labor market entry. However, in both exercises, Arcidiacono et al. and mine, the estimated wage overall effect of race decreases with experience. The reason of this decreasing estimated wage effect on the "black" dummy variable when it is allowed to vary with experience is that employers might be using legal reasons to pay African Americans lower (i.e. actual lower productivity levels than their white peers).

One striking difference between ABH's results and those obtained in this replication exercise is the volatile effects on the race interaction with experience. Particularly, specification 3 shows a sharp decrease of the race experience interaction coefficient (-.228) with respect to specification 2 (-.034). Furthermore, these two estimated wage effects on race greatly differ from that obtained by Arcidiacono et al. with their sample, which is -.126.

In summary, results for the college sample on race greatly differ from the prediction of the revelation of ability model based on EL-SD proposed by Arcidiacono et al. First, using their econometric specification, in which individuals with 16 years of schooling are considered college graduates, I did not obtain similar results to those reached by them. Second, using individuals that received a degree as college graduates also yields different results to those predicted by the revelation of ability model proposed by Arcidiacono et al. Although I am using slightly different data construction rules in specification (2) and (3) that lead to smaller samples, these differences in results suggest that their findings, at least for the college sample, are not as robust as they indicate in their paper[16].

[15] African American college graduates younger than 25 in the sample earn, on average, a log of real wage of 2.12 and score 0.21 standard deviations above sample average. On the other hand, whites earn, on average, 2.1 and score 1.01 standard deviations above the sample average.

[16] According to Light and McGee (2012), although Arciadocono et al. conclude that employer learning occurs only for less-schooled men, they found that employer learning differs across the two subsamples (high school and college graduates).

Table 4

Dependent Variable: Log Hourly Wage, OLS Estimates			
College Graduates - Non Hispanic sample			
Model	ABH College	Replication College Sample	
	(1)	(2)	(3)
Standardized AFQT	.142 **	.123 **	.159 **
	(.035)	(.037)	(.040)
Standardized AFQT *experience/10	.020	.177 *	.098
	(.047)	(.070)	(.072)
Black	.113 **	.089	.167
	(.054)	(.057)	(.060)
Black* experience/10	-.126 *	-.034	-.229 **
	(.068)	(.094)	(.098)
R^2	0.182	0.200	0.201
N observations	4,112	3,468	2,850
Education	16 years	16 years	degree

All specifications control for urban residence, region, a cubic in experience, and year effects. Specification in column (1) presents estimates reached by Arcidiacono's et al. for individuals that had 16 years of education when they first left school. Specification in columns (2) and (3) presents estimates reached in this replication exercise. In column (2) results for individuals that had 16 years of education and in column (3) estimates for college graduates that reported obtaining a degree are reported. Robust standard errors adjusted in the individual level.
* significant at the 5% level, **significant at the 1% level

4.2. Education's effect on wages

4.2.1. Altonji and Pierret

The overall effect of education on wages after ten years of experience can be decomposed in two parts:

$$\beta_{overall,edu} = \beta_{edu} + \beta_{edu,t}$$

where the first term (β_{edu}) is the initial effect of years of education at the moment of hire and the second term ($\beta_{edu,t}$) is the cumulative change of the effect of education after the worker has accumulated 10 years of experience.

In Table 5 the effects of education on wages in four different models are shown. Each of the specifications differs from the other in the hard-to-see *z* variable that was used. For instance, the first model uses AFQT scores as a *z* variable. In the second model, the log of the oldest sibling average real wage between year five to eight of experience is used instead. In the third model father's years of education is used as a *z* variable and, finally, in the fourth model all three of the variables (AFQT scores, sibling's wage and father's years of education) are included simultaneously. In these models, AP assume that sibling's wage and father's education are positively correlated with the individual's productivity, so their inclusion in the EL-SD model should follow the same logic as entering the standardized AFQT scores variable.

To compute results, two experience measures were used: potential and actual experience. The reason to include both measures of experience is that actual experience could be used as a productivity signal by employers as it reflects the amount of time spent in the labor market and, as a result, bias all effects in the regression. AP address this endogeneity issue by performing a two stage least square regression, in which they instrument actual experience with potential experience. Hence, all terms that include actual experience are treated as endogenous and instrumented with their potential experience equivalents. It is also worth mentioning that the potential and actual experience variable and father's education are divided by 10, so a unit increase in experience is equivalent to an increase of 10 years.

Results in Table 5 show a fundamental result related to statistical discrimination in the basis of education: the estimated overall effect of the *s* variable (education) does not increase with experience. This prediction follows for all specifications in Table 5, regardless of the measure of experience or *z* variable used.

Table 5

AP EL-SD Effects: Education Dependent Variable: Log Hourly Wage Non African American Sample								
z variable	Experience specification	Intial effect		Interaction with *t* effect		Effect after 10 years		N
AFQT scores	potential	.084	**	-.028	*	.056	**	16,572
		(.016)		(.014)		(.007)		
	actual	.113	**	-.091	**	.022	*	16,572
		(.024)		(.028)		(.010)		
Sibling's wage	potential	.066	**	-.007		.059	**	8,020
		(.019)		(.016)		(.011)		
	actual	.079	*	-.037		.042	**	8,020
		(.031)		(.035)		(.012)		
Father's education	potential	.074	**	-.005		.069	**	15,341
		(.015)		(.013)		(.009)		
	actual	.095	**	-.050		.045	**	15,341
		(.022)		(.026)		(.009)		
AFQT scores + Sibling's wage + Father's education	potential	.088	**	-.036	*	.052	**	16,572
		(.016)		(.014)		(.006)		
	actual	.112	**	-.096	**	.016	*	16,572
		(.023)		(.027)		(.007)		

Note: Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Hispanic interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. When the experience specification is potential experience, effects are obtained from an OLS regression. If the experience specification is actual experience, it is instrumented with potential experience and results are obtained from a 2SLS regression. Robust standard errors account for the multiple observations for each worker.
* significant at the 5% level, **significant at the 1% level

Similarly, the overall effect of a hard-to-see z variable on wages after ten years of experience can be decomposed in two parts:

$$\beta_{overall,z} = \beta_z + \beta_{z,t}$$

where the first term (β_z) is the initial effect of the hard-to-see z variable at the moment of hire and the second term ($\beta_{z,t}$) is the cumulative change in its total effect after 10 years of experience.

Hard-to-see z variables such as AFQT scores, sibling's wage and father's education are never directly observed by employers. Nonetheless, EL-SD theory implies that they are increasingly correlated with productivity as the worker gains experience. The initial effect of a z variable is in all cases not statistically different from zero, which is consistent with these variables not being observed (or valued) at the beginning of the worker's career and, consequently, not a determinant of his market entry wage. Alternatively, the cumulative change of the effect of the *z* variable is generally large. Consequently, results conform with the EL-SD prediction that the estimated impact of such z variables does not decrease with experience. When using actual experience instrumented with potential experience, the main direction of results remain unchanged.

Table 6

AP EL-SD Effects: z variables
Dependent Variable: Log Hourly Wage
Non African American Sample

z variable	Experience specification	Intial effect	Interaction with *t* effect		Effect after 10 years		N
AFQT scores	potential	-.010	.095	*	.085	**	16,572
		(.047)	(.040)		(.018)		
	actual	-.012	0.127		.115	**	16,572
		(.070)	(.080)		(.022)		
Sibling's wage	potential	-.052	.285	**	.233	**	8,020
		(.111)	(.098)		(.037)		
	actual	-.132	.428	*	.296		8,020
		(.428)	(.162)		(.407)		
Father's education	potential	.000	.106		.106	**	15,341
		(.110)	(.096)		(.040)		
	actual	.039	.073		.112	*	15,341
		(.150)	(.175)		(.047)		
AFQT scores	potential	-.022	.096	*	.074	**	16,572
		(.047)	(.040)		(.015)		
Sibling's wage		.046	.200	**	.246	**	
		(.041)	(.052)		(.030)		
Father's education		.000	.036		.036		
		(.104)	(.090)		(.039)		
AFQT scores	actual	-.018	.125		.107	**	16,572
		(.070)	(.080)		(.022)		
Sibling's wage		.056	.191	**	.247	**	
		(.046)	(.070)		(.043)		
Father's education		.025	.001		.026		
		(.149)	(.173)		(.047)		

Note: Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Hispanic interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. When the experience specification is potential experience, effects are obtained from an OLS regression. If the experience specification is actual experience, it is instrumented with potential experience and results are obtained from a 2SLS regression. Robust standard errors account for the multiple observations for each worker.
* significant at the 5% level, **significant at the 1% level

In summary, it can be said that the coefficients on *s* and *z* variables agree with EL-SD proposition when regressions use white and Hispanic males.

4.2.2. *Arcidiacono et al.*

Arcidiacono et al. propose an econometric specification which is equivalent to AP's preferred specification but performed separately for either the high school or college subsamples. Arcidiacono et al. believe that education can be used by workers to fully communicate their productivity to firms. Hence, high school graduates do not directly transmit information of their productivity but rather reveal it gradually as their job performance is observed in each period. On the other hand, they consider that college graduates nearly completely reveal their productivity to firms through their degree.

The effects of hard-to-see (z) variables on wages for four different models described in Table 7 are shown. The first and third models consider with 12 and 16 years of education. The second and fourth models consider high school and college degree recipients. Given the similarities between the models proposed by AP and Arcidiacono et al., predictions of the EL-SD model about z variables can be tested here. If the hypothesis proposed by Arcidiacono et al. that states that productivity for the high school sample is unknown but slowly revealed as the worker accumulates experience is true, the effect of ability (AFQT scores) should be non-decreasing with experience. Alternatively, if obtaining a college degree is a signal strong enough to satisfactory reveal the worker's actual productivity, then the effect of *z* should be non-increasing with experience.

Indeed, results in Table 7 show that a high school graduate scoring a standard deviation above average gets a small and statistically insignificant coefficient at market entry, while after ten years of experience, returns to AFQT scores are very large and statistically significant. This happens for all specifications on the high school sample, regardless of the definition of high school graduate or the experience measure used. Consequently, empirical effects predicted by the EL-SD model in the proposition about *s* and *z* variables are consistent with results for the high school sample when regressions use white and Hispanic men.

In the college sample, nonetheless, Arcidiacono et al. considered that college graduates nearly perfectly communicate their productivity to firms through information contained in a typical college graduate resume like grades, courses, college attended, among others. In general, effects do not follow the hypothesis proposed by Arcidiacono et al. Workers that have completed 16 years of education report a large, although imprecisely estimated, initial wage effect to scoring one standard deviation higher than average in the AFQT test. Furthermore, AFQT scores are associated with a large and statistically significant coefficient on its interaction with experience effect after ten years of experience. Similarly, college degree recipients show initial and cumulative change effects for AFQT scores of similar magnitude, reporting an increasing and statistically significant overall wage premium. Since college graduates report a large experience effect on *z*, it can be said that empirical predictions from Arcidiacono et al. do not apply to slight changes in the sample for Hispanic and white individuals. Conversely, the estimated effect of ability is not decreasing with experience, which conforms with the standard EL-SD predictions for *z* variables. A possible interpretation of these results would be that college graduates do communicate productivity to employers when they are first hired, but as time passes, those who score a standard deviation higher than average also get a large wage premium.

Table 7

ABH EL-SD Effects: AFQT scores as z variable
Dependent Variable: Log Hourly Wage
Non African American Sample

Education	Experience specification	Intial effect		Interaction with experience		Effect after 10 years		N
12 years of education	potential	.014		.096	**	.110	**	10,304
		(.014)		(.021)		(.017)		
	actual	.018		.097	**	.115	**	10,304
		(.014)		(.024)		(.019)		
High school diploma	potential	.014		.095	**	.109	**	7,849
		(.016)		(.024)		(.020)		
	actual	.007		.105	**	.112	**	7,849
		(.016)		(.028)		(.023)		
16 years of education	potential	.068		.242	**	.310	**	3,197
		(.045)		(.083)		(.064)		
	actual	.052		.234	**	.286	**	3,197
		(.049)		(.089)		(.064)		
College diploma	potential	.117	*	.111		.228	**	2,680
		(.049)		(.086)		(.064)		
	actual	.098		.111		.209	**	2,680
		(.053)		(.093)		(.064)		

Note: Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Hispanic interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. When the experience specification is potential experience, effects are obtained from an OLS regression. If the experience specification is actual experience, it is instrumented with potential experience and results are obtained from a 2SLS regression. Robust standard errors account for the multiple observations for each worker.
* significant at the 5% level, **significant at the 1% level

4.3. Ethnicity effect on wages

4.3.1. Altonji and Pierret

The main objective of this empirical exercise is to assess if their EL-SD model predictions about race can be extended to individuals of Hispanic ethnicity when compared with white individuals. It is noted by AP that race can be thought of as an easy-to-see *s* variable or it can act as a hard-to-see *z* variable. If Hispanic ethnicity is an *s* variable and if belonging to this particular group is believed to be associated with lower productivity levels, employers will use this information to set lower wages for Hispanics than for individuals of "preferred" ethnicities. Nonetheless, as firms observe signals of the worker's productivity in each period, the wage setting process will be based less on the employer's initial beliefs about the worker's ethnicity and more on new information about his productivity. In other words, the EL-SD model predicts that if Hispanic ethnicity is an *s* variable, its estimated initial impact is negative and increases toward zero with experience.

Contrariwise, if firms do not use Hispanic ethnicity as relevant productivity information at the initial wage setting process, even though they are able to directly observe it and use it to set wages, ethnicity has the properties of a *z* variable. The EL-SD model then predicts that, its initial effect should be less negative than if the employer would fully use ethnicity to statistically discriminate. Additionally, as the worker accumulates experience and his actual productivity is revealed, the estimated effect of the Hispanic interaction with experience should decrease because productivity information revealed to employers in each period becomes more important. In other words, employers may chose to ignore ethnicity at market entry but they acquire productivity information over time that may be used to differentiate wages among workers.

Similar to the case of *s* and *z* variables, the overall effect of the Hispanic ethnicity variable on wages after ten years of experience can be decomposed in two parts:

$$\beta_{overall,Hispanic} = \beta_{Hispanic} + \beta_{Hispanic,t}.$$

In Table 8 the effects of being Hispanic on wages in four different models are shown. The first model is AP's preferred specification, in which AFQT scores enter the model as a *z* variable. In the second model, the log of wage of the oldest sibling is used. In the third model father's years of education is the hard-to-see variable (z). In model four, all three of the *z* variables are included at the same time.

The effect being Hispanic for AP's specifications using different hard-to-see (z) variables follows a visible pattern: the initial effect to being a Hispanic individual starts out being negative and imprecisely estimated in all cases, results that leads to the conclusion that there is not statistically significant evidence of statistical discrimination in terms of wages against Hispanics upon labor market entry. The cumulative effect change of being Hispanic is positive and also statistically not different from zero across all specifications, which also shows that there are no statistically significant effects to being Hispanic as individuals accumulate experience. Although not statistically significant, direction of effects show that Hispanics start out with a negative wage gap in comparison to their white similar peers, which narrows with experience. These results support the EL-SD hypothesis that Hispanic ethnicity is an *s* variable.

Table 8

AP EL-SD Effects: Hispanic Ethnicity
Dependent Variable: Log Hourly Wage
Non African American Sample

***z* variable**	Experience specification	Intial effect	Interaction with experience	Effect after 10 years	N
AFQT scores	potential	-.115 (.095)	.094 (.078)	-.021 (.031)	16,572
	actual	-.180 (.142)	.215 (.161)	.035 (.036)	16,572
Sibling's wage	potential	-.005 (.118)	.011 (.096)	.006 (.041)	8,020
	actual	-.021 (.157)	.042 (.175)	.021 (.041)	8,020
Father's education	potential	-.111 (.109)	.077 (.092)	-.034 (.035)	15,341
	actual	-.168 (.175)	.177 (.184)	.009 (.081)	15,341
AFQT scores + Sibling's wage + Father's education	potential	-.082 (.100)	.087 (.082)	.005 (.032)	16,572
	actual	-.131 (.158)	.182 (.177)	.051 (.037)	16,572

Note: Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Hispanic interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. When the experience specification is potential experience, effects are obtained from an OLS regression. If the experience specification is actual experience, it is instrumented with potential experience and results are obtained from a 2SLS regression. Robust standard errors account for the multiple observations for each worker.
* significant at the 5% level, **significant at the 1% level

4.3.2. Arcidiacono et al.

The model proposed by Arcidiacono et al. helps us observe if there is statistical discrimination on the basis of the worker's ethnic identity for high school and college graduates and this situation evolves with employer learning. Results for the four different specifications are shown in Table 9.

For those individuals who have completed 12 years of education, the earnings differential between Hispanics and whites starts out small and negative. After spending 10 years in the labor market, the overall effect to being Hispanic gets closer to zero but it is statistically insignificant. Similarly, Hispanic individuals that have had obtained their high school degree when they first started working showed small and negative, although imprecisely estimated, wage gaps with respect to their white counterparts. Since the cumulative change in the total effect to being Hispanic after ten years is small and positive, the overall effect is small and statistically not different from zero. In general, it can be said that there is no strong empirical evidence of Hispanics being statistically discriminated against in terms of wages, neither at labor market entry nor after 10 years of experience regardless of which definition of high school graduate is used. Moreover, there is not a significant difference between OLS or IV estimated results.

In the college sample, Hispanics with 16 years of education show a positive and large, although imprecisely estimated, wage premium at the beginning of their careers. To explain the positive earnings differential between Hispanics and their similar white peers in the college market, it worth mentioning that the unconditional mean of real wages of Hispanics is higher than that of whites in this sample at market entry, although they score lower in the AFQT test[17]. Consequently, conditional on AFQT scores, it is not surprising that Hispanics show a positive, although imprecisely estimated, wage premium with respect to whites. On the other hand, the estimated cumulative change in the wage effect of being Hispanic after ten years spent on the labor market is very small and not statistically different from zero. As a result, the overall effect to being of Hispanic identity obtained for individuals that have completed 16 years of education is large but not statistically significant.

[17] Hispanic college graduates younger than 25 in the sample earn, on average, a log of real wage of 2.28 and score 0.78 standard deviations above the sample average. On the other hand, whites earn, on average, 2.1 and score 1.01 standard deviations above the sample average. It is worth mentioning that this same situation occurs between African Americans and whites in the exercised performed by Arcidiacono et al. in their non-Hispanic sample.

For workers in the college sample who obtained their diploma, the initial effect to being Hispanic is large but statistically not significant, while the experience effect is near zero and also imprecisely estimated. However, the overall effect after 10 years of experience for Hispanic individuals with a college degree is large and statistically significant at a 5% level. This would primarily mean that Hispanics appear to have a wage premium over their similar white peers. Furthermore, this shows that the learning effect of ethnicity on wages is sensitive to the definition of college graduate.

Table 9

ABH EL-SD Effects: Hispanic Ethnicity
Depedent Variable: Log Hourly Wage
Non African American Sample

Education	Experience specification	Intial effect	Interaction with experience	Effect after 10 years		N
12 Years of education	potential	-.005	.004	-.001		10,304
		(.030)	(.040)	(.033)		1,346
	actual	-.005	.006	.001		10,304
		(.028)	(.046)	(.037)		1,346
High school diploma	potential	-.041	.028	-.013		7,849
		(.036)	(.048)	(.040)		907
	actual	-.036	.022	-.014		7,849
		(.033)	(.054)	(.045)		907
16 years of education	potential	.101	.019	.120		3,197
		(.072)	(.110)	(.092)		459
	actual	.096	.010	.106		3,197
		(.075)	(.108)	(.083)		459
College diploma	potential	.149	.029	.178	*	2,680
		(.081)	(.111)	(.079)		377
	actual	.148	.006	.154	*	2,680
		(.084)	(.109)	(.073)		377

Note: Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Hispanic interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. When the experience specification is potential experience, effects are obtained from an OLS regression. If the experience specification is actual experience, it is instrumented with potential experience and results are obtained from a 2SLS regression. Robust standard errors account for the multiple observations for each worker.
* significant at the 5% level, **significant at the 1% level

Consistent with the other models presented above, there is not empirical evidence of statistical discrimination against Hispanics in the high school or in the college samples. Furthermore, the variable that indicates Hispanic ethnicity does not fit the pattern of an *s* nor *z* variable.

5. Conclusions

The main purpose of this study is to test if Hispanics male workers face discrimination when compared to their similar white peers at labor market entry and to observe how this situation evolves as they accumulate experience. In order to do this, using the NLSY 1979, I replicated AP's EL-SD empirical exercise that included African Americans and whites to conduct a robustness test of their EL-SD hypotheses. Indeed, employers appeared to statistically discriminate on the basis of education but not on the basis of race, which are also the main results in AP's paper.

Afterwards, I tried to assess if the main EL-SD predictions can be extended to Hispanic and white individuals. The first proposition about the impact of *s* and *z* variables holds for the non-African American sample since the estimated effect of the *s* variable is non-increasing with experience and the estimated effect of the *z* variable is non-decreasing with experience. This means that employers statistically discriminate on the basis of education. In the matter of ethnicity, results indicate that there is not statistically significant evidence of statistical discrimination against Hispanics. However, directions of effects obtained in this section show Hispanics start out with a negative wage gap in comparison to similar white individuals, which narrows toward zero as they accumulate experience. This fits with the hypothesis that Hispanic ethnicity is an *s* variable and, consequently, that Hispanic individuals are statistically discriminated against in terms of wages at market entry but the employer learning effect reduces the initial wage gap as he accumulates work experience. Nonetheless, it is worth noting that there might be other factors or types of discrimination that may explain race, or in this case, ethnic earnings differentials.

Using the revelation of ability model (Arcidiacono et al.), which is a variation of AP's EL-SD model, I try to answer another interesting question related to statistical discrimination: how do college diplomas communicate productivity information at labor market entry and how this situation evolves over time? In this model, I test if the revelation of ability model is robust to a slightly different data (AP's data set). In the high school sample, I found strong evidence that ability is gradually revealed as workers gain experience. On the other hand, the replication exercise fails to get similar results for race. Arcidiacono et al. obtained an initial negative wage gap that imprecisely expands with experience, whereas this replication exercise shows a much wider negative and which significantly grows with experience. As a result, none of these results supports the EL-SD hypothesis that race is an *s* variable.

More importantly, replication results for the college sample do not follow the revelation of ability model for race either. There are two ways in which I was unable to replicate results' reached by Arcidiacono et al. First of all, using their econometric specification, which consisted in using individuals who had completed 16 years of education, I was unable to reach their results. Second, using a more precise specification, which considers college graduates those who got a diploma at the end of their student careers, results also greatly differed from the empirical predictions of the revelation of ability model.

Arcidiacono et al. argues that college graduates almost perfectly reveal their ability to employers through their diploma at market entry and that this education effect should not vary with experience. On the contrary, results in my replication exercise show that ability is partially observed at labor market entry and also learned and valued by employers as worker´s ability is revealed through their job performance in each period. In the matter of race, both Arcidiacono et al. and my replication exercises obtained a large initial wage premium of African Americans with respect to whites in the college market, which is explained by similar wages between individuals of the two races at market entry, despite African Americans scoring less in AFQT tests than whites. Nonetheless, this positive wage gap decreases with experience in both exercises, which indicates that employers may be assessing worker´s differences in ability as they observe their performance. In brief, results on race are not conclusive about predictions of the revelation of ability model to both slightly different decisions on the construction of the data and different specifications of college graduate definition. Based on these two problems to mimic results from the revelation of ability model, I suggest their findings are not as robust as they indicate in their paper.

Afterwards, using AP's non-African American replicated data set, I mimic Arcidiacono et al. econometric specification to verify robustness of their results when comparing Hispanic and white male workers. This exercise basically helps us observe how individuals´ diploma communicates their ability to firms. Results in terms of the impact of ability seemed to be robust to slight changes in sample construction and the inclusion of Hispanic in the analysis for the high school sample. Indeed, high school graduates show non-decreasing effects to ability with experience, which means that they gradually reveal it to the labor market as their job performance is observed. These results did not seem to be sensitive to the definition of high school graduate or the experience measure used. Conversely, in the college sample, effects do not follow the hypothesis proposed by Arcidiacono et al., regardless of the definition of college graduate. The impact of ability was large at market entry and increased as experience was accumulated, which contradicts Arcidiacono et al. hypothesis of non-increasing effect of ability on wages for college graduates, which, in order words, discard their proposition that workers communicate ability to firms in a discrete lump. Although results for the college market were similar no matter what the measure of experience was being used, results differ for both definitions of college graduate.

In the matter of ethnicity, in the revelation of ability exercise I found no strong or statistically significant empirical evidence of statistical discrimination on the basis of ethnicity in the high school sample, results being small and imprecisely estimated both at market entry and as the worker accumulated experience. Furthermore, results did not vary greatly for different definitions of high school graduate or for the experience measure used in the analysis. In the college graduate sample, similar to the replication exercise of Arcidiacono et al., Hispanic also registered a positive and large wage premium at the beginning of their careers, mainly due to Hispanics earning higher wages than whites at market entry, although they score lower in the AFQT test. Initial results for Hispanic workers are large but statistically non-significant, while the experience effect is near zero and also imprecisely estimated. However, the overall effect, when using workers with college diplomas instead of those who completed 16 years of education, is large and significant, showing that effects of ethnicity on wages are sensitive to the definition of college graduate used.

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Mathematical Appendix I

a) *Summary of the EL-SD model proposed by AP [2001]*

Here I present the basic assumptions under which AP's EL-SD model is derived. The theoretical model that AP propose is the following:

$$y_{it} = rs_i + \alpha_1 q_i + \Lambda z_i + \eta_i + H(t_i)$$

where y_{it} is the log of labor market productivity and its four main components: s_i are variables that are observed by both the employer and the econometrician, q_i are variables that are observed or used by the employer but not by the econometrician, z_i are variables that are seen or used by the econometrician but not by the employer, η_i is an index that makes up for determinants of productivity that are not directly seen by the employer and unknown or not used by the econometrician. Employers do not see z_i or η_i but they have conditional expectations of them that are linear on *q* and *s*:

$$z_i = E(z_i \mid s_i, q_i) + v = \gamma_1 q_i + \gamma_2 s_i + v_i$$

$$\eta_i = E(\eta_i \mid s_i, q_i) + e = \alpha_2 s_i + e_i$$

where v_i and e_i are error terms.

Plugging z_i and η_i in y_{it}, it is clear that $\Lambda v_i + e_i$ is the error term of the employer's conditional expectation of the log of labor market productivity at the beginning of the worker's career, which is, by definition, uncorrelated with s and q.

Furthermore, each period of time employers see an inexact signal of the worker's productivity $\xi_{it} = y_i + \varepsilon_{it}$, where $y_i = y_{it} - H(t_i)$. ε_{it} is independent from the other variables in the model by construction and is equivalent to temporal variations of the worker's productivity and effects of changes in the firm that makes it difficult to the employer to evaluate the worker.

Employers observe q_i, s_i and ε_{it}, so they also observe $d_{it} = \xi_{it} - E(y_i \mid s_i, q \ ) = \varepsilon_{it} + \Lambda v_i + e$, which is sum of the error of the imprecise signal of the worker's productivity ε_{it} at each period plus the error of the conditional expectation of worker's productivity at market entry. There is a vector $D_{it} = \{d_{i1}, d_{i2}, d_{i3}, ..., d_{it}\}$, which contains information about the worker's performance in each period of time.

The wage paid to the employee is the expectation that firms have of the worker's productivity, conditional on what they observe (s_i, q_i and D_{it}): $W_{it} = E(Y_{it} \mid s_i, q_i, D_{it}) \exp^{\xi_{it}}$ where Y_{it} is a function of the worker's productivity $\exp^{Y_{it}}$ and $\exp^{\xi_{it}}$ is said to account for measurement error and other firm characteristics that are uncorrelated to q_i, s_i and D_{it}.

The log of wage is, then:

$$\ln(W_{it}) = (r + \Lambda\gamma_2 + \alpha_2)s_i + H^*(t_i) + (\alpha_1 + \Lambda\gamma_1)q_i + E(\Lambda v_i + e_i \mid D_{it}) + \xi_{it}$$

where $H^*(t_i) = H(t_i) + \log(E(\exp^{\mu_{it}}))$. The $E(\Lambda v_i + e_i \mid D_{it})$ term is the expected value of the error term of the worker's log of productivity at labor market entry conditional on his performance in each period, which means that, based on D_{it}, employers can change their initial valuation of the worker's productivity.

According to the econometrician point of view, the expected value of the log of wage conditional on s_i, z_i and t is the following:

$$E[\ln(W_{it})] = b_{st} s_i + b_{zt} z_i + H^*(t)$$

where AP assumes $H^*(t)$ to be orthogonal to s_i, z_i, and q_i. However, $(\alpha_1 + \Lambda\gamma_1)q_i$ and $E(\Lambda v_i + e_i \mid D_{it})$ are only observed by employers, which causes the formula above to have omitted variable bias. According to the omitted variable bias formula, the coefficients b_{st} and b_{zt} would be equal to:

$$b_{st} = b_{s0} + \Phi_{st} = [r + \Lambda\gamma_2 + \alpha_2] + \Phi_{qs} + \Phi_{st}$$

$$b_{zt} = b_{z0} + \Phi_{zt} = \Phi_{qz} + \Phi_{zt}$$

Where Φ_{qs} and Φ_{qz} are the coefficients of the regression $(\alpha_1 + \Lambda\gamma_1)q_i$ on s_i and z_i; and Φ_{st} and Φ_{zt} are the coefficients of the regression of $E(\Lambda v_i + e_i \mid D_{it})$ on s_i and z_i.

It is possible to express Φ_{st} as $\theta_t \Phi_s$, and Φ_{zt} as $\theta_t \Phi_z$, where Φ_s and Φ_z are the coefficients of the regressions of $\Lambda v_i + e_i$ on s_i and z_i, and

$$\theta_t = \frac{\operatorname{cov}(E(\Lambda v_i + e_i \mid D_{it}), z_i)}{\operatorname{cov}(\Lambda v_i + e_i, z_i)} = \frac{\operatorname{cov}(E(\Lambda v_i + e_i \mid D_{it}), v_i)}{\operatorname{cov}(\Lambda v_i + e_i, v_i)}$$

The signs on Φ_s, Φ_z, and the experience path θ_t will determine the signs on b_{st} and b_{zt}. AP empirically show that $\Phi_s < 0$, $\Phi_z > 0$ if $\operatorname{cov}(\Lambda v_i + e_i, v_i) > 0$ and $\operatorname{cov}(s_i, z_i) > 0$. If s_i is equivalent to years of education and z_i to AFQT scores, log of sibling's wage or father's education, AP maintain that the covariance of *s* and *z* is positive. AP also state that the fact that $\operatorname{cov}(\Lambda v_i + e_i, v_i) > 0$, which is the covariance of the error term of the employer's conditional expectation of the log of the worker's productivity at the beginning of their career with the error of the worker's unobservable characteristics *z*, is plausible.

The experience path θ_t shows the rate at which the employer learns about the worker's productivity, which is bounded between 0 and 1. The parameter θ_t is 0 at the beginning of the worker' career, since the employer does not know anything about $\Lambda v_i + e_i$. Conversely, θ_t is 1 if $E(\Lambda v_i + e_i \mid D_{it})$ is equal to $\Lambda v_i + e_i$, which means that the employer has learned all there is to know about the worker's productivity.

b) Summary of the revelation of ability model proposed by Arcidiacono et al. [2010]

Arcidiacono et al. present a model of statistical discrimination that, similar to AP. The log of labor market productivity of a worker is equal to the following formula:

$$\chi_{it} = f(s_i) + \lambda_t (q_i + z_i + \eta_i) + \tilde{H}(t_i)$$

where $f(s_i)$ is the effect of schooling on productivity, q_i is relevant information about the worker that is observed by the employer but not by the econometrician, z_i is a proxy measure for ability (correlate of productivity) that is observed by the econometrician but not directly by the employer, η_i is information about the worker not observed by the employer nor by the econometrician, λ_t is the coefficient on (q_i, z_i, η_i) and $\tilde{H}(t_i)$ is a function of experience.

Arcidiacono et al. assume that $\widetilde{H}(t_i)$ is independent of s_i and z_i and the productivity signals employers get as the worker accumulate experience. Employers use the information they have available to predict χ_{it}. Variable z_i is orthogonal to η_i and q_i. The fact that z_i is uncorrelated to η_i is intuitive since employers see neither of the two at the beginning of the worker's career.

Furthermore, there is evidence in the data that it is not possible to predict z_i with the information employers see in the initial period (q_i). Arcidiacono et al. also assume that (q_i, s_i, z_i, η_i) is jointly normally distributed, which means that a linear combination of its components has a univariate normal distribution. The following formula expresses the conditional expectation of $\eta_i \mid (s_i, q_i)$:

$$\eta_i = \alpha_1 s_i + \alpha_1 q_i + v$$

Arcidiacono et al. assume that, although employers do not observe z_i, they do observe the average ability of the worker's group $z_i = E(z_i \mid s_i, t_i, race_i)$. Employers estimate $z_i = z + e_i$, variable that they plug into $\chi_{it} = f(s_i) + \lambda_t (q_i + z + e_i + \eta_i) + \widetilde{H}(t_i)$. Then, the log of labor market productivity at the initial period is equal to $\chi_{i0} = rs + \lambda_0 (q_i + z + e_i + \eta_i) + \widetilde{H}(0)$, which is equal to $\chi_{i0} = E(\chi_{i0} \mid z, q_i) + \lambda_0 (e_i + \eta_i)$, where $\lambda_0 (e_i + \eta_i)$ is the "expectation error" employers have about the worker's productivity at the beginning of the worker's career.

As employers observe each period's signal of the worker's productivity $(y_{it} = z_i + \eta_i + \varepsilon_{it})$, the expectation error will tend to decrease. In period 0, the mean of the initial evaluation of the worker can be expressed as $\mu_0 = z + \alpha_1 s_i + \alpha_1 q_i$ and in any following period as $\mu_{it} = (1 - \theta_t)\mu_{i,t-1} + \theta_t y_{it}$, where θ_t is a Bayesian weight that is set initially. The term μ_{it} continues to be updated while firms observe the successive outputs the employer generates.

The expected productivity of a worker at time t is then:

$$E_{it}(\chi_{it} \mid z, q_i, s_i, Y_i^t) = rs_i + \lambda_t q_i + \lambda_t [(1 - \theta_t)\mu_{i,t-1} + \theta_t y_{it}] + \widetilde{H}(t_i)$$

where $Y_i^t = \{y_{i1},...,y_{it}\}$. As the employer realizes the true productivity of the worker by observing the signals of his output over time, the term $[(1-\theta_t)\mu_{i,t-1} + \theta_t y_{it}]$ converges to the true value of $z_i + \eta_i$.

The wage is the expected productivity of a worker: $W_{it} = E_{it}[\exp(\chi_{it}) \mid z, q_i, s_i, Y_i^t]$. Consequently, the log of wage can be expressed as: $\log(W_{it}) = \lambda_t[(1-\theta_t)\mu_{i,t-1} + \theta_t y_{it}] + C_{it}$ where $C_t = rs_i + \lambda_t q_i + \tilde{H}(t) + \frac{\sigma_t^2}{2}$.

This function of the log of wage is conditioned to variables (z, q_i, s_i, Y_i^t). However, we do not observe q_i nor Y_i^t, so it needs to be expressed in variables that are observed by us (z, z_i, s_i, t). In order to do this, we need to express these variables that we do not have knowledge about as linear projections of what we do know: $q_i = \gamma_1 s_i + u_1$ and $\eta_i = \gamma_2 s_i + u_1$. Consequently, the log of wages can also be expressed as:

$$E^*[\log(W_{it}) \mid z, s] = \lambda_t[(1-\theta_t)E^*(\mu_{i,t-1} \mid z_i, s_i) + \theta_t E^*(y_{it} \mid z_i, s_i)] + c_{it}$$

where $c_{it} = rs_i + \lambda_t(\gamma_1 s_i + u_i) + \tilde{H}(t_i) + \frac{\sigma_t^2}{2}$. Replacing $\mu_{i,t}$ in $E^*[\log(W_{it}) \mid z, s]$, the log of wages in period 1 is: $\log(W_{i1}) = \lambda_1[(1-\theta_1)z + \theta_1 z_i] + k_{i1}$, where $k_{it} = \lambda_1(1-\theta_1)[\alpha_1 s + \alpha_1(\gamma_1 s + u_1) + \theta_1(\gamma_2 s + u_1 + \varepsilon_{i1})] + c_1$.

In period 1, the log of wage is the weighted average of the mean ability of the worker's group z and actual ability, plus a constant. This constant k_{it} shows that early beliefs of employers are based on schooling, q_i, and η_i.

For periods in time greater than 1, the log of wages is:

$$\log(W_{it}) = \lambda_1[\prod_{i=1}^{t}(1-\theta_1)z + \left[1 - \prod_{i=1}^{t}(1-\theta_1)\right]z_i] + k_{it}$$

where $k_{it} = \lambda_{it} \prod_{i=1}^{t} (1-\theta_t)[\alpha_1 s_i + \alpha_1(\lambda_1 s_1 + u_t)] + \left[1 - \prod_{i=1}^{t}(1-\theta_t)\right](\gamma_2 s + u_1 + \varepsilon_{i1}) + c_{it}$. As long as the employer observes productivity signals from the worker, $\prod_{i=1}^{t}(1-\theta_t) \to 0$ because employer learning parameter θ_t increases. This means that every period, more weight will be given to actual ability z_i and less to the mean ability of the worker's group z.

Appendix II

Employer Learning-Statistical Discrimination for non-Hispanic males 1979-1992 using potential experience as the experience measure

Table 10

Effects of Standarized AFQT and Schooling on Wages for non-Hispanics

Dependent Variable: Log Hourly Wage, OLS Estimates (SE)

Panel 1 - Experience measure: potential experience

Variable	(1)		(2)		(3)		(4)	
Education	.065	**	.089	**	.070	**	.085	**
	(.012)		(.015)		(.012)		(.015)	
Black	-.126	**	-.126	**	.027		-0.034	
	(.026)		(.026)		(.064)		(.071)	
Standarized AFQT	.093	**	-.002		.093	**	.024	
	(.015)		(.037)		(.015)		(.042)	
Education	-.008		-.029	*	-.001		-.025	
*experience/10	(.010)		(.012)		(.001)		(.013)	
Standarized AFQT			.085	**			.061	
*experience/10			(.031)				(.035)	
Black*experience/10					-.136	**	-.082	
					(.052)		(.060)	
R^2	0.2973		0.298		0.2981		0.2985	
N individuals	2,761		2,761		2,761		2,761	
N observations	18,407		18,407		18,407		18,407	

Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, hlack interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. Robust standard errors account for the multiple observations for each worker.

* significant level at the 5% level

**significant level at the 1% level

Employer Learning-Statistical Discrimination for non-Hispanic males 1979-1992 using actual experience as the experience measure and instrumented with potential experience

Table 11

Effects of Standarized AFQT and Schooling on Wages for non-Hispanics

Dependent Variable: Log Hourly Wage, 2SLS Estimates (SE)

Panel 2 - Experience measure: actual experience instrumented by potential experience

Variable	(1)		(2)		(3)		(4)	
Education	.088	**	.121	**	.096	**	.118	**
	(.019)		(.022)		(.018)		(.023)	
Black	-.081	**	-.079	**	.086		-.009	
	(.027)		(.026)		(.090)		(.112)	
Standarized AFQT	.105	**	-.019		.103	**	.003	
	(.015)		(.051)		(.014)		(.063)	
Education *experience/10	-.062	**	-.100	**	-.069	**	-.010	**
	(.022)		(.027)		(.022)		(.003)	
Standarized AFQT *experience/10			.147	*			.121	
			(.059)				(.075)	
Black*experience/10					-.205		-.087	
					(.108)		(.137)	
R^2	0.3128		0.313		0.3126		0.313	
N individuals	2,761		2,761		2,761		2,761	
N observations	18,407		18,407		18,407		18,407	

Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, hlack interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. Robust standard errors account for the multiple observations for each worker.

* significant level at the 5% level

**significant level at the 1% level

Employer Learning-Statistical Discrimination for the non-Hispanics 1979-1992 with sibling's Wage and father's education as hard-to-see (z) variables

Table 12

Effects of Father's Education, Sibling Wages and Schooling on Wages for Non-Hispanics

Dependent Variable: Log Hourly Wage; OLS Estimates (SE)

Experience Measure: Potential Experience

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	.053 **	.063 **	.059 **	.066 **	.076 **	.080 **	.079 **	.081 **
	(.016)	(.017)	(.016)	(.017)	(.013)	(.013)	(.013)	(.013)
Black	-.185 **	-.187 **	-.018	-.053	-.188 **	-.187 **	-.031	-.036
	(.030)	(.096)	(.096)	(.100)	(.026)	(.026)	(.070)	(.074)
Log of sibling's wage	.203 **	.030	.208 **	.059				
	(.034)	(.096)	(.034)	(.100)				
Father's education/10					.088 *	.009	.088 *	.065
					(.039)	(.099)	(.039)	(.105)
Education * experience/10	.009	-.001	.004	-.003	-.001	-.005	-.004	-.005
	(.014)	(.015)	(.014)	(.014)	(.011)	(.011)	(.011)	(.011)
Log of sibling's wage * experience/10		.165 *		.141				
		(.085)		(.088)				
Father's education * experience/100						.073		.022
						(.084)		(.089)
Black * experience/10			-.148	-.119			-.140 *	-.135 *
			(.083)	(.086)			(.059)	(.063)
R^2	0.333	0.334	0.334	0.335	0.285	0.285	0.2858	0.2858
N individuals	1,257	1,257	1,257	1,257	2,439	2,439	2,439	2,439
N observations	8,943	8,943	8,943	8,943	16,370	16,370	16,370	16,370

Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Black interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For specifications (1) to (4) sibling's gender and log of sibling's wage is interacted with a cubic time trend. For specifications (5) to (8) father's education is interacted with a cubic time trend For the time trends, the base is 1992. Robust standard errors account for the multiple observations for each worker.

* significant level at the 5% level

**significant level at the 1% level

Employer Learning-Statistical Discrimination 1979-1992 with AFQT scores, sibling wage, father's education, and schooling

Table 13

Effects of Standarized AFQT, Father's Education, Sibling Wages and Schooling on Wages for Non-Hispanics

Dependent Variable: Log Hourly Wage; OLS Estimates (SE)

Experience Measure: Potential Experience

Variable	(1)		(2)		(3)		(4)	
Education	.061	**	.090	**	.067	**	.084	**
	(.012)		(.015)		(.012)		(.015)	
Black	-.100	**	-.097	**	.092		.033	
	(.026)		(.026)		(.063)		(.070)	
Standarized AFQT	.087	**	-.016		.087	**	.018	
	(.016)		(.039)		(.016)		(.042)	
Log of sibling's wage	.154	**	.060		.159	**	.067	
	(.021)		(.038)		(.021)		(.038)	
Father's education/10	.028		.045		.030		.067	
	(.038)		(.098)		(.038)		(.100)	
Education * experience/10	-.007		-.033	**	-.011		-.027	*
	(.010)		(.012)		(.010)		(.013)	
Standarized AFQT * experience/10			.092	**			.062	
			(.032)				(.035)	
Log of sibling's wage * experience/10			.131	**			.126	**
			(.047)				(.047)	
Father's education * experience/100			-.021				-.042	
			.084				(.085)	
Black * experience/10					-.170	**	-.117	*
					(.052)		(.060)	
R^2	0.310		0.312		0.311		0.3124	
N individuals	2,761		2,761		2,761		2,761	
N observations	18,407		18,407		18,407		18,407	

Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, black are interacted with a cubic time trend, AFQT interacted with a cubic time trend, log of sibling's wage is interacted with a cubic time trend, father's education is interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. Also included are sibling's gender and dummy variables to contro for whether father's education is missing and whether sibling's wage is missing, and interactions between these dummy variables and experience when experience interactions are included. For the time trends, the base is 1992. Robust standard errors account for the multiple observations for each worker.

* significant level at the 5% level

**significant level at the 1% level

Table 14

Effects of Standarized AFQT on Log Wages for High School and College Graduates - Non-Hispanic sample

	High School				College			
Model	(1)		(2)		(3)		(4)	
AFQT	.012		.011		.123	**	.159	**
	(.013)		(.015)		(.037)		(.040)	
AFQT *experience/10	.105	**	.099	**	.177	*	.098	
	(.020)		(.023)		(.070)		(.072)	
Black	-.039		-.055		.089		.167	**
	(.027)		(.031)		(.057)		(.060)	
Black* experience/10	-.097	*	-.092	*	-.034		-.228	*
	(.038)		(.043)		(.094)		(.098)	
R^2	0.159		0.173		0.200		0.201	
N individuals	1,627		1,129		500		403	
N observations	11,965		9,301		3,468		2,850	

All specifications control for urban residence, region, a cubic in experience, and year effects. In specifications (1) and (3) high school and college graduates have 12 or 16 years of education, respectively, when they first left school. In specifications (2) and (4) high school and college graduates reported having a degree when they first left school. Robust standard errors adjusted in the individual level.
* significant level at the 5% level
**significant level at the 1% level

Employer Learning-Statistical Discrimination for all males 1979-1992 using actual experience as the experience measure and instrumented with potential experience

Table 15

Effects of Standarized AFQT and Schooling on Wages for the complete sample

Dependent Variable: Log Hourly Wage, OLS Estimates (SE)

Panel 1 - Experience measure: potential experience

Variable	(1)		(2)		(3)		(4)	
Education	.059	**	.087	**	.062	**	.086	**
	(.011)		(.014)		(.011)		(.014)	
Black	-.129	**	-.129	**	.008		-.088	
	(.025)		(.025)		(.064)		(.069)	
Hispanic	-.005		-.006		-.058		-.108	
	(.029)		(.029)		(.091)		(.093)	
Standarized AFQT	.094	**	-.021		.094	**	-.015	
	(.014)		(.035)		(.014)		(.039)	
Education *experience/10	-.006		-.031	**	-.007		-.029	*
	(.009)		(.012)		(.009)		(.012)	
Standarized AFQT *experience/10			.101	**			.097	**
			(.029)				(.033)	
Black*experience/10					-.120	*	-.035	
					(.052)		(.058)	
Hispanic*experience/10					.043		.088	
					(.074)		(.076)	
R^2	0.280		0.281		0.281		0.282	
N individuals	3,244		3,244		3,244		3,244	
N observations	21,991		21,991		21,991		21,991	

Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Black interacted with a cubic time trend, Hispanics interacted with a cubic time trend, AFQT interacted with a cubic time trend, 2-digit occupation at first job, and urban residence. For the time trends, the base is 1992. Robust standard errors account for the multiple observations for each worker.

* significant level at the 95% level

**significant level at the 99% level