

Beyond Signaling and Human Capital: Education and the Revelation of Ability[†]

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We provide evidence that college graduation plays a direct role in revealing ability to the labor market. Using the NLSY79, our results suggest that ability is observed nearly perfectly for college graduates, but is revealed to the labor market more gradually for high school graduates. Consequently, from the beginning of their careers, college graduates are paid in accordance with their own ability, while the wages of high school graduates are initially unrelated to their own ability. This view of ability revelation in the labor market has considerable power in explaining racial differences in wages, education, and returns to ability. (JEL D82, I21, I23, J24, J31)

In traditional models of ability signaling (A. Michael Spence 1973; Andrew Weiss 1995), education provides a way for individuals to sort into groups (education levels) that are correlated with ability. Employers use education to statistically discriminate, paying wages that depend in part on the average ability of the individuals with the same level of education. Building on these models, Henry S. Farber and Robert Gibbons (1996) and Joseph G. Altonji and Charles R. Pierret (2001) develop a framework in which employers do not initially observe the ability of a worker, but learn about it over time. As employers gather more information about the ability of a worker, they rely less on education and more on the new information in determining the wages. In these dynamic learning models, education serves as a tool for workers to signal their unobserved ability, although its role in determining wages decreases with experience.

In this paper, we argue that education (specifically attending college) plays a much more direct role in revealing ability to the labor market. Rather than simply sorting individuals into broad ability groups, our results suggest that college allows individuals to directly reveal key aspects of their own ability to the labor market. Following in the tradition of the employer learning literature, the evidence that we provide is based on an examination of the returns to ability over the first 12 years

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of an individual's career.¹ Specifically, using data from the National Longitudinal Survey of Youth (NLSY), we show that the returns to the Armed Forces Qualification Test (AFQT), our measure of ability, are large for college graduates immediately upon entering the labor market, and do not significantly change with labor market experience. In contrast, returns to AFQT for high school graduates are initially very close to zero and rise steeply with experience. These results suggest that key aspects of ability are observed nearly perfectly for college graduates, but are revealed to the labor market more gradually for high school graduates.

There are a number of potential factors that likely contribute to ability revelation in the college labor market. Resumes of recent college graduates typically include information on grades, majors, standardized test scores, and, perhaps even more importantly, the college attended.² In this way, our analysis leaves open the possibility that sorting of individuals across colleges may play a significant role in the revelation of ability in the college market. It does, however, imply a more limited role of educational attainment per se in signaling (as opposed to revealing) ability in the college market.³

The insight that ability is revealed in the college market but not in the high school market has a great deal of power in explaining racial wage differences. In the college market, consistent with the notion that ability is almost perfectly revealed, we find that, if anything, blacks earn *more* than whites in the college market.⁴ The lack of evidence for statistical discrimination in the college market is especially noteworthy given the large differences in the AFQT distributions for college-educated blacks and whites.⁵ In contrast, we estimate that blacks initially earn 6 percent to 10 percent less than whites with the same AFQT scores in the high school labor market. Such a wage difference would arise naturally if employers use race to statistically discriminate when setting wages in the high school market. These results then provide an alternative explanation for the finding of David Bjerk (2007) that blacks earn significantly less in blue collar occupations than whites, but there is no racial wage gap in white-collar occupations.

These results on the evolution of racial wage differences also provide a compelling explanation for the fact that, conditional on ability, blacks obtain more education than whites (Neal and William R. Johnson 1996; Lang and Michael Manove 2006, LM, hereafter). Facing a wage penalty in the high school labor market (possibly due to statistical discrimination), but not in the college labor market, blacks clearly have

¹ The main analysis presented in the paper limits the sample to males. Conducting a similar analysis for females is slightly more complicated due to greater concerns about selection into the labor market. Preliminary results for females that use the procedure outlined in Derek Neal (2004) to deal with selection reveal similar patterns to those for males.

² In the analysis presented below, we show that this type of information explains a large portion of the variation in AFQT scores.

³ This has important consequences for the large empirical literature that examines the extent to which the college wage premium is due to productivity enhancement versus ability sorting. See, for example, Hanming Fang (2006), Altonji and Pierret (1998), Fabian Lange (2007), Orley Ashenfelter and Alan B. Krueger (1994), Weiss (1995), Kevin Lang (1994), Joseph E. Stiglitz (1975); Jacob A. Mincer (1974), and Gary S. Becker (1964). Our analysis also naturally suggests a reinterpretation of the findings of the employer learning literature following Altonji and Pierret (2001).

⁴ That blacks earn a premium in the college market is being driven by particularly high AFQT blacks. This may be due to affirmative action in the labor market operating most heavily where blacks are the scarcest.

⁵ The mean AFQT for blacks is approximately one standard deviation lower than that of whites in both the high school and college samples.

stronger incentives to obtain a college degree than whites with comparable AFQT scores.⁶

The rest of the paper is organized as follows. Section I gives a general overview of the data we use for our empirical analysis. Section II presents our main empirical findings, which consist of a series of wage regressions. To fully interpret these findings, Section III uses the resulting coefficients to estimate a simple model of employer learning and statistical discrimination. Section IV presents some additional specifications of our main estimating equations and Section V concludes.

I. Data

The data used in this study are drawn from the 1979–2004 waves taken from NLSY79. In selecting the sample, we follow the criteria used in Altonji and Pierret (2001) and Lange (2007) as closely as possible. Our main analysis is restricted to white or black men who have completed 12 or 16 years of education, i.e., who have exactly a high school or a college degree. We consider a respondent to have entered the labor market the moment that he reports to have left school for the first time. Actual experience is the weeks worked divided by 50, and potential experience is defined as years since the respondent first left school.⁷ If the respondent leaves the labor market and goes back to school, we subtract the added years of schooling from the experience measures. Military jobs, jobs at home, or jobs without pay are excluded from the construction of experience and from the analysis.

The wage variable is the hourly rate of pay at the most recent job from the Current Population Survey (CPS)⁸ section of the NLSY.⁹ In order to make our measure of ability, the AFQT, comparable across individuals, we standardize the AFQT score to have a mean zero and standard deviation one for each age at which the test was taken.¹⁰ We use data from the main and the supplementary sample of the NLSY79, which oversamples blacks and disadvantaged whites.¹¹

We restrict the sample to observations where potential experience was less than 13 years. The reason for this, as explained in the Web Appendix that replicates Joseph G. Altonji and Charles R. Pierret (AP hereafter), is that there exists a nonlinear

⁶ Another possibility is that the AFQT is racially biased. With a racially biased test, blacks would be more likely to attend college conditional on AFQT, all else being equal. While it is very difficult to identify whether a test is racially biased, Neal and Johnson (1996) note that the AFQT has been subject to rigorous examination to ensure that it is a racially fair test. Further, if ability was higher for blacks once we netted out AFQT, we would expect blacks to perform better in college than whites. After controlling for SAT (which has received much more attention for racial bias than the AFQT), blacks still have much lower grade point averages than whites (see Julian R. Betts and Darlene Morell 1999).

⁷ Lange (2007) argues that this way of constructing potential experience captures time spent in the labor market better than age minus education minus seven.

⁸ The CPS is a section of the NLSY79 that includes variables that establish activity during the survey week, job characteristics, global job satisfaction, hourly pay, and hours worked per week for the current/most recent job and job search behavior.

⁹ The real wage is created using deflators from the 2006 Economic Report of the President. We limit real wages to more than \$1 and less than \$100 per hour.

¹⁰ Here, we use the original definition of AFQT. We also estimated analogous specifications to those reported in the paper using AFQT89, which weights the underlying ASVAB sections that make up the AFQT differently. This had no effect on our results.

¹¹ All of the statistics in this study are unweighted. As shown in the Web Appendix, using the sampling weights has no effect on the qualitative results.

TABLE 1—SUMMARY STATISTICS FOR COLLEGE AND HIGH SCHOOL GRADUATES BY RACE

	Blacks			Whites		
	Total	High school grad	College grad	Total	High school grad	College grad
Observations	7,177	6,070	1,047	16,449	11,976	4,473
AFQT						
Mean	−0.663	−0.839	0.358	0.484	0.253	1.102
SD	0.877	0.769	0.762	0.805	0.784	0.460
Urban residence (%)	83.40	81.83	92.52	72.59	68.67	83.08
Region (%)						
Northeast	14.79	15.23	12.24	21.38	20.22	24.49
North Central	15.64	14.81	20.46	35.60	36.71	32.63
South	62.54	63.94	54.40	28.31	28.09	28.92
West	7.03	6.02	12.91	14.70	14.98	13.96
Log of real wage						
Ages < 25	6.47	6.45	6.84	6.61	6.58	6.83
Ages 25–30	6.65	6.58	7.02	6.88	6.80	7.07
Ages 30–35	6.71	6.61	7.13	7.02	6.91	7.26
Ages > 35	6.80	6.71	7.23	7.13	6.98	7.45
<i>Actual experience</i>						
Cum. weeks worked/52						
Ages < 25	2.42	2.46	1.71	2.75	2.87	1.82
Ages 25–30	5.51	5.73	4.48	5.97	6.59	4.72
Ages 30–35	8.73	8.67	8.88	9.56	9.71	9.27
Ages > 35	12.20	12.03	13.03	13.54	13.21	14.20
<i>Potential experience</i>						
Years since left school						
Ages < 25	3.37	3.46	1.76	3.30	3.52	1.54
Ages 25–30	7.67	8.28	4.70	7.16	8.40	4.56
Ages 30–35	12.36	12.95	9.69	11.89	13.20	9.30
Ages > 35	17.41	18.00	14.46	17.02	18.21	14.57

Notes: Individual-by-year observations coming from a panel from 1979–2004. In terms of individuals, we have 1,917 whites and 798 blacks.

relationship between log wages, AFQT, and potential experience. In order to keep the analysis simple, we focus on the approximately linear region of this relation. This region seems to correspond to experience levels less than 13. Another reason for this sample selection is attrition in the NLSY79, which implies that the number of observations falls noticeably with experience. A more detailed explanation of the sample construction is given in the Web Data Appendix.

Table 1 summarizes the main variables in our sample. Notable from Table 1 are the differences in AFQT scores for blacks and whites of the same education level. For both college and high school graduates, this gap extends to about one standard deviation of the AFQT population distribution. It is also clear from the table that conditional on age, blacks generally earn lower wages and accumulate less labor market experience than whites.

An important exception to the general pattern of racial differences in wages in Table 1 is the fact that blacks and whites earn almost identical wages at the time of initial entry into the college labor market. At first glance, this unconditional statistic may seem surprising given that the average AFQT scores of college-educated whites

are about a standard deviation higher than those of their black counterparts.¹² As shown in Arcidiacono, Bayer, and Hizmo (2008), this pattern is driven by the fact that college-educated blacks in the top decile of the AFQT distribution earn a substantial initial wage premium that declines to zero over the first ten years of labor market experience. We return to a more detailed discussion of racial differences in wages later in the paper.

II. Baseline Results

Given limited information, employers have incentives to rely on easily observed characteristics such as education and race to assess the productivity of a potential worker. In pure signaling models of education (Spence 1973; Weiss 1995) education serves as a (costly) mechanism for workers to sort on ability. Employers then use the average group ability of the education level to which the worker belongs to determine wages. In many cases race can also be a predictor of ability, so employers use race when determining wages.

The employer learning literature argues that if AFQT is not directly observable by firms, it will have a limited relationship to initial wages. As workers spend more time in the labor market, employers become better informed about their ability, leading to an increased correlation between wages and AFQT with experience. As employers learn directly about ability, they need to rely less on correlates of ability and, therefore, the returns to education decline over time. These predictions have been shown to hold in Altonji and Pierret (2001) and Farber and Gibbons (1996). We replicate the main results of AP using our sample and present their results in the Web Appendix.

In this paper, we argue that education is more than a tool for workers to signal their ability. Our hypothesis is two-fold: that employers learn slowly about the ability of high school graduates, and that ability is directly revealed for college graduates. If our hypothesis is true, pooling all education levels in wage regressions can lead to biases and the misinterpretation of the results. Examples of papers that pool all the education levels and analyze employer learning and statistical discrimination include AP, Thomas K. Bauer and John P. Haisken-DeNew (2001), Farber and Gibbons (1996), Fernando Galindo-Rueda (2003), and Lange (2007). We test our hypothesis and analyze racial differences in wages and returns to ability by splitting the sample into college and high school graduates. We formulate a simple econometric model similar to that of AP, and estimate it separately for each of the two education levels. For each group, the log wage equation is

$$\begin{aligned}
 (1) \quad w_i = & \beta_0 + \beta_2 r_i + \beta_{AFQT} AFQT_i + \beta_{r,x} (r_i \times x_i) + \beta_{AFQT,x} (AFQT_i \times x_i) \\
 & + \beta_{r,AFQT} (r_i \times AFQT_i) + \beta_{r,AFQT,x} (r_i \times AFQT_i \times x_i) + f(x_i) \\
 & + \beta_{\Phi}' \Phi_i + \varepsilon_i.
 \end{aligned}$$

¹² Using census data, Neal (2006) also documents that college-educated blacks and whites initially have similar wages upon entering the labor market.

TABLE 2—THE EFFECTS OF AFQT ON LOG WAGES FOR HIGH SCHOOL AND COLLEGE GRADUATES

Model	High school		College		Test: College=HS P-values	
	(1)	(2)	(3)	(4)	(5)	(6)
Standard. AFQT	0.0060 (0.0130)	0.0078 (0.0129)	0.1485** (0.0350)	0.1420** (0.0354)	0.000	0.000
AFQT × exper/10	0.1261** (0.0176)	0.1183** (0.0173)	0.0122 (0.0480)	0.0198 (0.0472)	0.026	0.050
Black	−0.0628** (0.0267)	−0.0483* (0.0259)	0.1098* (0.0563)	0.1125** (0.0543)	0.006	0.007
Black × exper/10	−0.0358 (0.0350)	−0.0340 (0.0345)	−0.1304* (0.0694)	−0.1264* (0.0677)	0.223	0.255
R ²	0.1631	0.1874	0.1678	0.1821		
Observations	11,795	11,772	4,112	4,112		
Additional controls	No	Yes	No	Yes	No	Yes
Experience measure: Years since left school for the first time <13						

Notes: All specifications control for urban residence, a cubic in experience, and year effects. Specifications (2) and (4) also control for region of residence and for part-time versus full-time jobs. In specification (5), we report the p-values for the difference in the coefficients of specifications (1) and (3). Similarly, specification (6) compares (2) and (4). The White/Huber standard errors in parenthesis control for correlation at the individual level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Log wages of individual i , w_i , are given as a linear interacted function of race r_i , AFQT, experience x_i , and other controls Φ_i . In all of our specifications, we control for urban residence and for year fixed effects. We also report White-Huber standard errors that take into account correlation at the individual level over time.

A. Education and Learning

Following the interpretation of AP, if employers do not initially observe ability, but learn about it over time, the weight placed on AFQT should be small initially and increase with experience. This means that β_{AFQT} should be close to zero, and $\beta_{AFQT,x}$ should be positive and sizable. On the other hand, if employers directly observe AFQT, the returns to AFQT should be high initially and should not change much over time. This case translates to a large β_{AFQT} and a relatively small $\beta_{AFQT,x}$. We estimate equation (1) separately for high school and college graduates and present the results in Table 2. Because we are working with log wages, β_{AFQT} is the percent change in real wages as a response to an increase of AFQT by one standard deviation. We divide the interaction of any variable with experience by 10 so the coefficient $\beta_{AFQT,x}$ is the change in the wage slope between the periods when $x = 0$ and $x = 10$.

Specification (1) in Table 2 estimates equation (1) for our high school sample by setting $\beta_{r,AFQT}$ and $\beta_{r,AFQT,x}$ to zero. This is the equivalent specification of AP for our high school sample. The coefficient on $AFQT$ is very small and statistically insignificant, suggesting that there are no returns to AFQT at the time of initial entry into the labor market. This is consistent with the view that AFQT is not readily observable to employers when they set wages.

In contrast, the coefficient on AFQT interacted with experience is positive and significant. The coefficient estimate implies that an individual with 10 years experience would see an increase in wages of almost 13 percent from a one standard deviation increase in AFQT. The results do not change under specification (2), which includes additional controls for region of residence and part-time jobs. These results for the high school sample are consistent with standard hypothesis put forth in the employer learning literature. Employers initially observe ability imperfectly, but learn about it over time.¹³

Specifications (3) and (4) of Table 2 repeat the same empirical exercise for the college market, revealing a very different experience profile for the returns to AFQT. In specification (3), the coefficient on *AFQT* is large and statistically significant while the coefficient on *AFQT* \times *exper/10* is small and not statistically significant. In contrast to the high school sample, there are substantial returns to AFQT immediately upon entry into the labor market. A one standard deviation increase in AFQT is associated with an almost 15 percent increase in wages. Moreover, the returns to AFQT are only slightly affected by experience, rising only an additional percentage point after ten years. Interpreted through the lens of the employer learning literature, this AFQT-experience profile suggests that employers observe AFQT nearly perfectly at the time of initial entry into the college labor market and learn very little additional information with experience.¹⁴

In specifications (5) and (6) of Table 2, we test if the coefficients presented are significantly different in the college market versus the high school market. Specification (5) presents the *P*-values of the difference between specification (1) and (3). We find significant differences between the college and high school coefficients for *AFQT* and *AFQT* \times *exper/10*. Similar results can be seen in specification (6) where we include additional controls. Overall, it is clear from all specifications that there are significant differences between the college and high school samples in both the initial returns to AFQT and its experience profile.

B. How College Reveals AFQT

There are a number of potential factors that likely contribute to ability revelation in the college labor market. Resumes of recent college graduates, for example, typically include information on grades, majors, standardized test scores, and, perhaps even more importantly, the college from which the individual graduated. Some of this information likely to be found on resumes is available to us, so we attempt to understand how it reveals underlying ability. We do not have information on grades

¹³ There is another potential explanation for the AFQT-experience profile revealed in specifications (1) and (2) of Table 2. In particular, the observed profile may simply reflect the actual impact of AFQT on the productivity of high school graduates as they gain experience in the labor market. Perhaps AFQT does not matter for the entry-level jobs performed by high school graduates, but matters more as workers gain experience. We take up this issue formally in Section III, where we develop a model of employer learning and statistical discrimination.

¹⁴ While AFQT represents only a single dimension of ability, remarkably similar patterns emerge for an alternative correlate of ability—father's education. Controlling for father's education shows the same qualitative patterns. It does not correlate with high school wages initially, but becomes correlated over time, while in college the correlation starts strong and does not change over time. Although all the patterns are the same as with AFQT, the estimates were generally noisy and only sometimes significant.

TABLE 3—PREDICTING THE AFQT FOR COLLEGE ATTENDEES

Dep. variable: AFQT	(1)	(2)	(3)	(4)
SAT Math sect./10	0.0258** (0.0031)			
SAT Verbal sect./10	0.0093** (0.0035)			
PSAT Math sect./10		0.2403** (0.0257)		
PSAT Verbal sect./10		0.0686** (0.0251)		
ACT Math sect./10			0.2862** (0.0449)	
ACT Verbal sect./10			0.3434** (0.0676)	
Years in college	0.0121 (0.0268)	0.0145 (0.0217)	−0.0013 (0.0216)	0.1560** (0.0159)
R ²	0.7024	0.6225	0.6494	0.3940
Observations	224	311	276	1,173

Note: All the specifications above are interacted with race and 24 college major dummies.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

or the quality of the college attended, but standardized test scores such as the SAT, PSAT, and ACT that we observe should serve as a proxy for college quality.

Table 3 displays the coefficient estimates for regressions of AFQT on college major, years in college, and standardized test scores interacted with race. We are interested in the general fit of the regressions rather than in the individual coefficients. The R^2 in specifications (1)–(3) ranges from 0.6225 when we control for PSAT scores to 0.7024 when we control for SAT scores. The number of the observations in these regressions, however, is low since these test scores are available for very few college graduates in the NLSY79. In specification (4), we include only years in college and major fixed effects interacted with race. The R^2 here is lower than when we include test scores, but it is still at a sizable magnitude of 0.3940. Overall, these regressions, which include variables describing only some of the information contained on a typical resume of individuals who attended college, indicate that this dimension of ability may be essentially revealed at the time of initial entry into the labor market.

C. Racial Differences

Racial Differences in Wage Profiles.—There are significant differences in the average AFQT of whites and blacks in both the high school and college samples. As shown in Figure 1, the mean and the median of the black distribution lie about one standard deviation below the white distribution for both high school and college graduates.¹⁵ Indeed, the median AFQT score for blacks who graduate from college

¹⁵ Similar findings about achievement test gaps are documented earlier in the literature. See Neal (2006) for a detailed discussion.

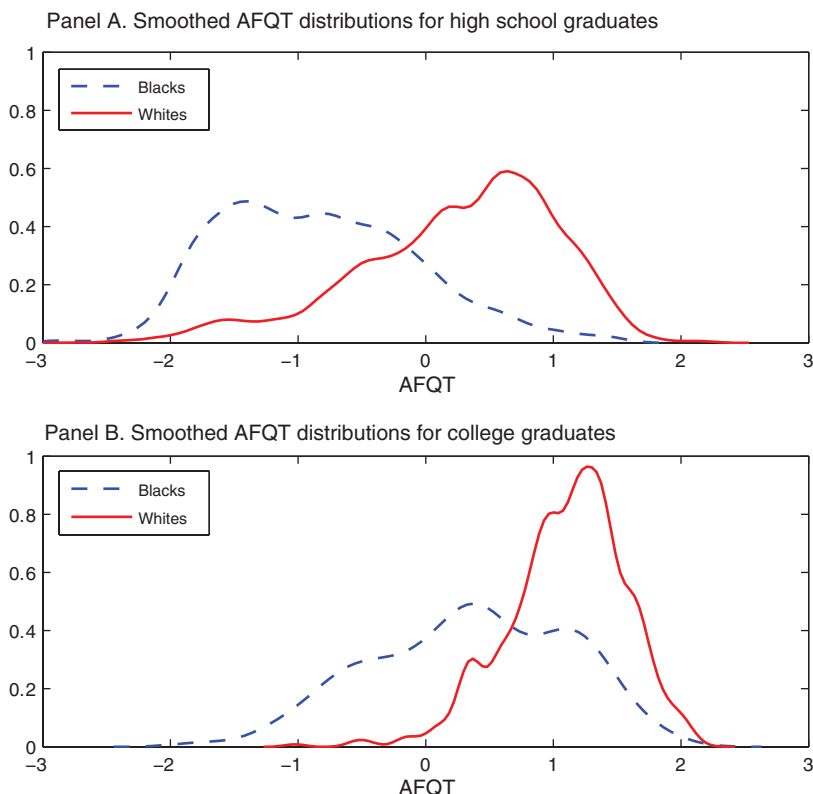


FIGURE 1. AFQT DISTRIBUTIONS BY RACE AND EDUCATION

equals the median AFQT score for whites who only attend high school. As a result, if employers do not directly observe ability, there are strong economic incentives to statistically discriminate on the basis of race.

Given the results for employer learning discussed in Section IIB, we would expect the incentives for statistical discrimination to be strong in the high school market, where ability is initially unobserved. This is reflected in the results presented in Table 2, which imply that blacks earn wages that are about 6 percent lower than those received by whites with the same AFQT score at the time of initial entry into the labor market. This gap increases (insignificantly) with labor market experience so that the estimated racial wage gap at 10 years of experience, conditional on AFQT, is 10 percent.¹⁶

¹⁶ That the racial wage gap in the high school market increases with experience is inconsistent with standard models of employer learning and statistical discrimination (see, for example, AP 2001). These models would predict that employers should weight race less as they learn more directly about worker productivity. In Section III, we formulate and estimate a model of employer learning and statistical discrimination that can accommodate an increasing racial wage gap. Our model differs from the existing models in that it allows for the true productivity of AFQT to change with experience. We decompose the coefficients on *Black* and *AFQT* into the part that comes from employer learning, and the part that comes from the true productivity of AFQT increasing over time. We find that AFQT becomes more important for productivity over time, and this generates increasingly stronger incentives for

Conversely, given the results for employer learning, we would expect incentives for statistical discrimination to be weak in the college market, as ability appears to be nearly perfectly observed at the time of entry into the college market. Specification (3) in Table 2 shows that, conditional on AFQT, college-educated blacks earn 11 percent *higher* wages than their white counterparts upon initial entry into the labor market.¹⁷ This premium declines to zero after about nine years of labor market experience.¹⁸ It is important to note here that the black college premium does not become negative after ten years, but is a result of imposing linearity on the experience interaction.

The results reported in Table 2 strongly suggest that statistical discrimination is not present in the college market. This fits well with the notion that college reveals ability. The lack of statistical discrimination in the college market is especially remarkable given the sizable differences in the distributions of AFQT between whites and blacks.

It is important to emphasize that the existence of an initial wage premium for college-educated blacks, conditional on ability, is a robust feature of the US labor market. Using much larger samples drawn from US census data and the CPS, Neal (2006) shows that college-educated blacks and whites have similar wages at the time of initial entry into the labor market. Given racial differences in average AFQT scores, this pattern implies the existence of a substantial black wage premium.

Explaining Racial Differences in Education Attainment.—LM report that, conditional on AFQT, blacks obtain more education than whites.¹⁹ Having documented this key empirical fact, LM attempt to explain it.²⁰ They develop a model in which employers generally observe a noisier signal for blacks than whites, but this racial difference in precision declines with education. This mechanism certainly provides an increased incentive for blacks to earn more education but also implies that, conditional only on AFQT, blacks should earn more than whites, an implication generally not supported by the data.²¹ Statistical discrimination arises through a different channel in our model. We do not need the crucial assumption made in LM that employers observe a noisier signal for blacks. In our view, statistical discrimination arises because employers have some idea of the racial differences in the AFQT

employers to statistically discriminate. If employers decide to statistically discriminate, the racial wage gap may indeed widen with experience.

¹⁷ In Arcidiacono, Bayer, and Hizmo (2008), we show that much of the large initial premium and its sharp decline is mainly driven by especially high wages of a small number of blacks in the top decile AFQT distribution.

¹⁸ The asymmetry of racial differences in the college and high school markets documented here is similar to results reported in Arcidiacono (2005). Using the NLS72 sample and analogous controls, Arcidiacono (2005) finds that blacks that attend at least some college earn more than their white counterparts, while blacks with a high school degree earn less, all else equal.

¹⁹ A similar result can be seen for our sample in Figure 1, which reports the AFQT distributions for blacks and whites in both high school and college. This fact has important implications for how one thinks about racial wage differences, implying, for example, that estimating the black-white wage gap properly requires one to control for both AFQT and education.

²⁰ LM first rule out differences in school quality as a potential explanation. They reason that because blacks generally attend lower quality schools, they may require more education in order to reach a given level of cognitive ability. They conclude, however, that school quality differences, while present, cannot possibly explain the observed racial differences in educational attainment.

²¹ Neal and Johnson (1996) show that, conditional on only AFQT, the racial wage gap is smaller, but blacks continue to earn less than otherwise identical whites.

distributions in Figure 1. In Arcidiacono, Bayer, and Hizmo (2008), we test if there are any racial differences in the initial signal observed and in employer learning by adding interactions of race with $AFQT$ and $AFQT \times \text{experience}$. We did not find any significant differences in the returns to $AFQT$ between whites and blacks in either the high school or college samples though the results are noisy.

The view of the labor market suggested by our main findings provides a related and more direct explanation for why blacks obtain more education than whites with the same $AFQT$ score. Facing statistical discrimination in the high school labor market, where ability is initially unobserved, blacks have a greater incentive to enter the college labor market and thereby revealing their $AFQT$. Thus, education symmetrically improves the precision of the signals that employers get for blacks and whites, but, because the value of that increased precision is greater for blacks, blacks obtain more education.²²

D. Structural Change at College Graduation

Here, we investigate whether there is a discrete jump in our coefficients of interest at college graduation. To do this we estimate a similar model to that of AP where we pool all education levels 8–20 in the same regression and include linear interactions of education with all the variables. In order to test for a structural shift at college graduation, we interact our variables of interest with an indicator variable that takes the value of 1 if the individual has 16 or more years of education. To make comparisons between these results and the results in Table 2, we subtract 12 from years of education, so that when education is zero, we get back results for the high school market.

The baseline coefficients, as well as their interactions with education and education greater than or equal to 16, are presented in Table 4. The baseline effects are similar to those for the high school market found in Table 2. Namely, $AFQT$ is uncorrelated with wages initially, but becomes correlated with experience, and blacks face a significant wage penalty. None of the education interactions shown in column 2 are statistically significant. In contrast, column 3 shows evidence of a statistically significant shift in the $AFQT$, $AFQT \times \text{exper}/10$, and black coefficients, but not in the coefficient on $Black \times \text{exper}/10$. The same patterns emerge as in Table 2, with strong initial returns to $AFQT$ for college graduates that change little as individuals acquire experience. Further, black college graduates see a wage premium the first few years in the labor market.

Figure 2 presents graphical evidence of the shift in parameters following college graduation. Here, we split the sample into 4 education levels: high school dropouts (9–11 years of education), high school graduates (12 years of education), college dropouts (13–15 years of education), and college graduates (16 years of educa-

²² Our explanation is also consistent with the fact that, conditional on only $AFQT$, blacks earn lower wages than whites, on average. In the college labor market, our results suggest that blacks earn more than whites with identical $AFQT$ scores, while in the high school labor market blacks at least initially earn 6 percent less than identical whites regardless of their $AFQT$ score. On average, whites can earn more than blacks with the same $AFQT$ score, provided that the college attendance of blacks is not enough to offset the wage penalty that blacks face in the high school market.

TABLE 4—TESTING FOR STRUCTURAL BREAK AT COLLEGE GRADUATION

Interacted with:	None	Education	$I(Educ \geq 16)$
Standard. AFQT	0.0148 (0.0109)	−0.0109 (0.0066)	0.1874** (0.0437)
AFQT × exper/10	0.1061** (0.0508)	0.0084 (0.0089)	−0.0939* (0.0508)
Black	−0.0504** (0.0211)	0.0102 (0.0145)	0.1658** (0.0771)
Black × exper/10	−0.0587** (0.0265)	−0.0018 (0.0179)	−0.0369 (0.0857)
R^2	0.3080		
Observations	25,692		
Experience measure: Years since left school for the first time < 13			

Notes: In order to make the baseline coefficients in the first column comparable to Table 2, we subtract 12 from our education measure. We pool all education levels, −4 to 8, and estimate a pooled version of specification (1) in Table 2 by adding linear interactions of education with everything (Education column). We also interact our four variables of interest with a dummy that equals 1 if education is bigger or equals 16 ($I(Educ=16)$ column). The White/Huber standard errors in parenthesis control for correlation at the individual level.

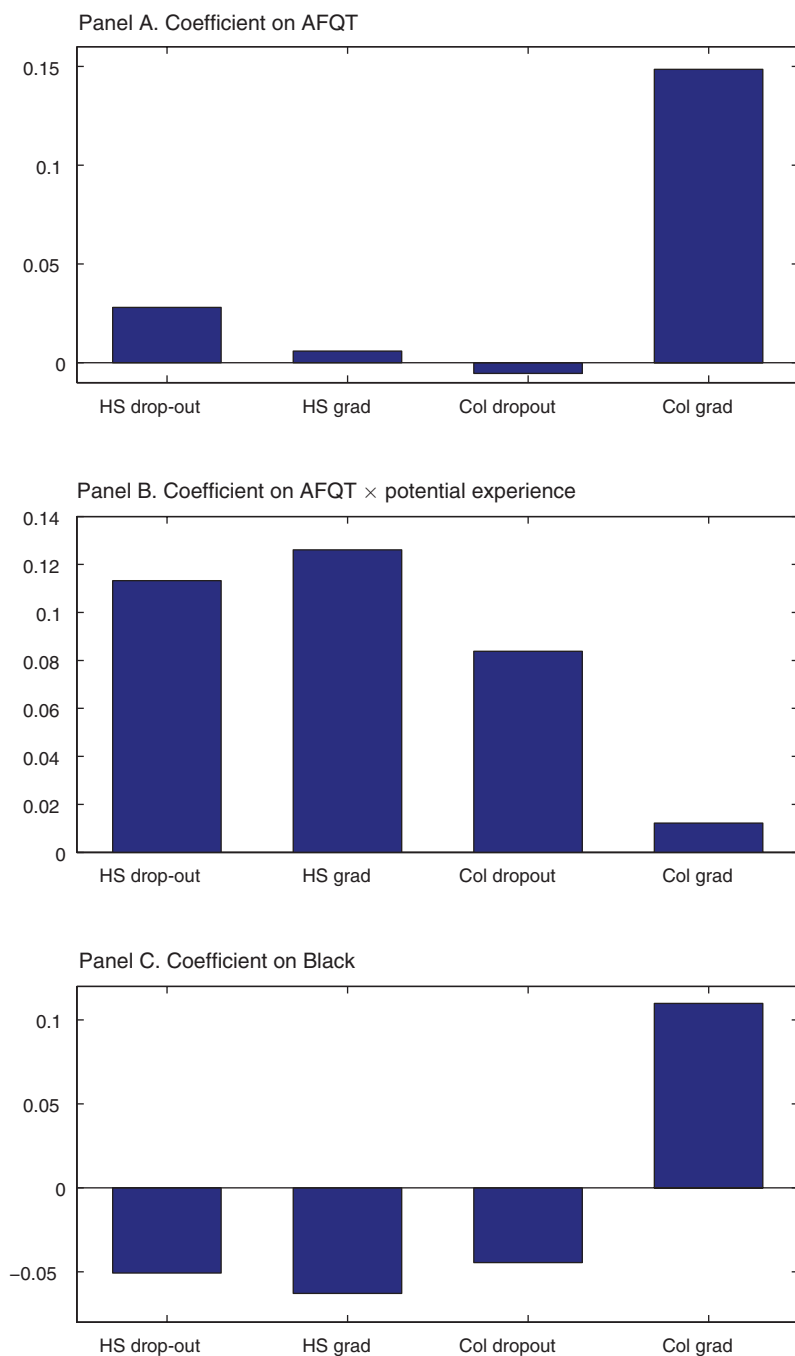
**Significant at the 5 percent level.
*Significant at the 10 percent level.

tion). We estimate the parameters separately for each group and for the categories that include more than one level of education we also include controls for years of education.²³ Again, the same patterns emerge for both the relationship between race and wages and the relationship between AFQT and wages, with college being a clear turning point in the relationships.

III. Statistical Discrimination

We argue that our results for the high school sample can be reconciled with statistical discrimination on the basis of race.²⁴ One scenario that rationalizes an increasing racial wage gap under the existence of statistical discrimination is the case when the true returns to AFQT increase with experience.²⁵ This is motivated by the intuition that AFQT should be more important for jobs further down the career path rather than for jobs taken upon initially entering the labor market. Under this scenario, blacks would be paid less initially since employers do not observe ability and therefore put weight on average group productivity. But because the true productivity of AFQT is increasing with time, employers have even stronger incentives to statistically discriminate over time. Thus, even though employers might learn about the productivity

²³ The results are not sensitive to whether we control for years of education.
²⁴ There could be other reasons why the wage gap between blacks and whites increases with experience such as increasing taste-based discrimination or racial differences in on-the-job training. Without ruling out these explanations, we focus on whether the observed patterns can be explained by statistical discrimination alone.
²⁵ One may argue that if the true returns to AFQT are increasing in the high school market, why would they not also increase in the college market? As we will show, the true returns to AFQT level off in the high school market after 10 years of experience. Hence, obtaining ten years of experience after high school puts those in the high school market in the same types of jobs as those who receive a college degree.

FIGURE 2. PLOTS OF COEFFICIENTS ON AFQT, AFQT \times POTENTIAL EXPERIENCE, AND BLACK

Note: There are 2,471, 11,795, 5,090, and 4,112 observations in each of the education categories starting from high school dropouts to college graduates.

of their workers to some degree, they might increase the weight they put on race with time as a result of the increased incentive to statistically discriminate.

We estimate a model of statistical discrimination that incorporates the insights developed in this scenario. We estimate the model for the high school sample where employer learning appears to be relevant. The starting point for our model is the standard employer learning model formalized by Farber and Gibbons (1996). A model of learning closely related to ours is developed in Lange (2007). Lange (2007) estimates the speed of employer learning assuming symmetrical learning and a competitive labor market. We maintain these crucial assumptions in our specification. Our model differs from existing models in that we allow the true productivity of AFQT to vary over time for the reasons given above.²⁶

The goal of this section of the paper is to study the implications for the speed of employer learning and the true productivity of AFQT over the early career, assuming that the observed racial wage differences are driven entirely by statistical discrimination. Assuming that racial wage differences are driven entirely by statistical discrimination obviously rules out taste-based discrimination and other potential explanations for the wage gap. In discussing the results below, we describe how they would change if the wage gap was partially due to these other factors.

The model, which is fully described in the Mathematical Appendix, yields an estimating equation that relates log wages to a linear function of both an individual's own ability (which is initially unobserved), $AFQT$, and the mean ability of his race, \overline{AFQT} . A key assumption, common in the statistical discrimination literature, is that average ability for each race is known. The weight placed upon individual $AFQT$ may increase over time for two reasons: employers learn about the individual's ability, and the true productivity of ability may also increase with experience.

We define the weights that the employer places on the individual's own ability and on the average ability of the individual's race at experience level x be given by Θ_x and $(1 - \Theta_x)$, respectively. We also define λ_x to be the true productivity of AFQT at experience level x . In the Mathematical Appendix, we show that, under certain assumptions regarding the nature of learning and what employers initially know, log wages follow:

$$(2) \quad w_x = \lambda_x \{ (1 - \Theta_x) \overline{AFQT} + \Theta_x AFQT \} + k_x,$$

where k_x is an experience-specific constant.

This representation of log wages has an intuitive interpretation. Log wages are a function of experience plus a weighted average of mean group ability, \overline{AFQT} , and actual ability, $AFQT$. The first source of the weight put on \overline{AFQT} and $AFQT$ comes from employers learning over time. If employers initially do not observe anything that is correlated to $AFQT$, they rely on group averages to set wages. In this case $\Theta_x = 0$, so all the weight is put on \overline{AFQT} . As employers observe more signals about

²⁶ Returns to AFQT could also change for reasons that are not captured in our model. If, for example, training is positively correlated with AFQT, the effect of additional training would resemble an increase in the true productivity of AFQT in our model.

the productivity of the worker, the weight will gradually be shifted from the group mean to the individual's ability.²⁷ In the Mathematical Appendix, we show that as experience increases, $\Theta_x \rightarrow 1$. The rate of this convergence, which is also the speed of learning, will depend on the quality of the signals that employers get every period.

The other part of the weight put on \overline{AFQT} and $AFQT$ comes from the true productive value of ability. This time-varying true productive value is captured by the parameter λ_x . As argued above, suppose ability is not as important for productivity for initial jobs as it is for jobs later in the career. In this case, λ_x will be low initially and increase over time, which means that additional weight will be put on both \overline{AFQT} and $AFQT$ as time passes. If the true productive value of $AFQT$ increases rapidly enough, the weight on $AFQT$ can actually increase over time despite the fact that direct learning would naturally tend to decrease it. As long as λ_x increases faster than the speed of learning, such that $\lambda_x(1 - \Theta_x) > \lambda_{x-1}(1 - \Theta_{x-1})$, more and more weight will be put on group average ability \overline{AFQT} .

We are only interested in the case of high school graduates, so education is held constant at 12. This means that we could estimate equation (2) directly by regressing log wages on mean $AFQT$ for each race and $AFQT$ for each experience level separately similar to Lange (2007):

$$(3) \quad w_{i,x} = \beta_{x,\overline{AFQT}} \overline{AFQT}_{race} + \beta_{x,AFQT} AFQT + \beta'_\Phi \Phi_{i,t} + \beta_x + \varepsilon_x.$$

The parameter β_x captures the effect of the variables observed only by the employer previously denoted by k_x . Also, $\Phi_{i,t}$ represents the demographic characteristics of a particular worker.

We can rewrite (3) as a function of the *Black* indicator variable rather than a function of \overline{AFQT}_{race} . In particular, we can rewrite the first term on the right-hand side of (3) as:

$$(4) \quad \begin{aligned} \beta_{x,\overline{AFQT}} \overline{AFQT}_{race} &= \beta_{x,\overline{AFQT}} (\overline{AFQT}_{black} - \overline{AFQT}_{white}) Black \\ &\quad + \beta_{x,\overline{AFQT}} \overline{AFQT}_{white} \\ &= \beta_{x,Black} Black + \beta_{x,\overline{AFQT}} \overline{AFQT}_{white}. \end{aligned}$$

Note that \overline{AFQT}_{black} and \overline{AFQT}_{white} are the same for everyone. Letting

$$(5) \quad \beta_x^* = \beta_x + \beta_{x,\overline{AFQT}} \overline{AFQT}_{white},$$

we can write the wage equation as:

$$(6) \quad w_{i,x} = \beta_{x,Black} Black + \beta_{x,AFQT} AFQT + \beta'_\Phi \Phi_{i,t} + \beta_x^* + \varepsilon_x.$$

²⁷ Similarly, employers distribute some weight on education initially, which decreases over time as employers learn more about ability. This education profile is captured in k_x . We do not pay particular attention to this since we are interested in statistical discrimination on the basis of race and not education.

This means that instead of including \overline{AFQT}_{race} in equation (3), we could include a dummy variable that takes value one if the worker is black, and zero otherwise, and still be able to estimate the parameters $\beta_{x,\overline{AFQT}_{race}}$ and $\beta_{x,AFQT}$. In this case, $\beta_{x,AFQT}$ would be unchanged and $\beta_{x,\overline{AFQT}_{race}} = \beta_{x,Black} / (\overline{AFQT}_{black} - \overline{AFQT}_{white})$.

This provides a structural interpretation of the coefficient on *Black* in the regressions presented earlier in the paper. Employers put weight on race for two reasons: the first part $(1 - \Theta_x)$ is related to learning about ability, and the second part, λ_x , comes from the changing productivity value of this ability. The size and the sign of the coefficient on *Black* depends entirely on the experience profile of λ_x and Θ_x . Empirically, as can be seen in Table 1, the difference between the mean of AFQT for whites and blacks is 1.0922 for high school graduates. After estimating equation (6), we can then solve for λ_x and Θ_x :

$$(7) \quad \lambda_x = \beta_{x,AFQT} - \beta_{x,Black} / 1.0922.$$

$$(8) \quad \Theta_x = \frac{\beta_{x,AFQT}}{\beta_{x,AFQT} - \beta_{x,Black} / 1.0922}.$$

We estimate equation (6) in one step by interacting *Black* and *AFQT* with a cubic in experience instead of estimating it separately for each experience level.²⁸ The estimation results are presented in Figure 3. The first two plots display the estimated coefficients on *Black* and *AFQT* for each experience level as well as the 90 percent confidence interval. The initial racial difference in wages is about 5 percent, and it increases to 10 percent in about 10 years. The effect of a 1 standard deviation increase in AFQT starts at 0 initially and increases to about 15 percent after 12 years of experience. These results are very similar to those previously shown in Table 2.

We use these experience profiles to calculate how much of the changes in the returns to race and AFQT, and how much of changes in the true productive value of AFQT can be attributed to employer learning. Panels C and D of Figure 3 plot the learning parameter Θ_x and the parameter λ_x , which captures the evolution of the productivity of AFQT over time. The learning parameter starts near 0, and by 12 years, increases to 0.6, which means employers observe 60 percent of AFQT in about 12 years. The true productivity of AFQT is also increasing with experience. A 1 standard deviation increase in AFQT leads to a 6 percent increase in productivity initially, which increases to about 24 percent in 12 years.

The weight put on race in the wage regression as a result of employer learning is given by $(1 - \Theta)$. This weight starts at 1.0 and declines to 0.4 after 12 years of experience. Initially employers do not observe ability, so they rely heavily on the race of the worker to determine wages. As they learn about individual worker productivity over time, their incentives to statistically discriminate decrease, and they rely less on race and more on the observed part of AFQT. This, however, does not mean that the actual return on race decreases with experience. Because the true

²⁸ Estimating this equation for each experience level separately, and smoothing the results, yields almost identical results. We interact *Black* and *AFQT* with a cubic in experience instead for ease of presentation.

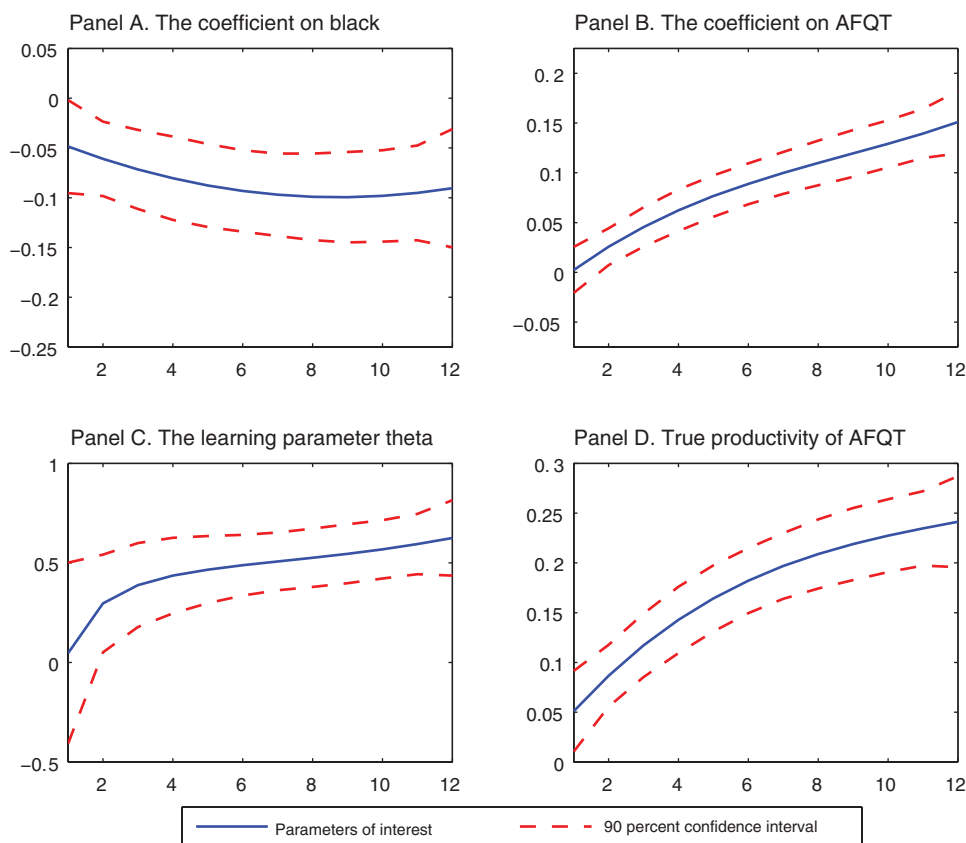


FIGURE 3. THE EVOLUTION OF THE EFFECT OF RACE AND AFQT ON WAGES, THE LEARNING PARAMETER Θ_x , AND THE TRUE PRODUCTIVITY OF AFQT, λ_x .

return to AFQT, λ_x , increases over time, employers actually have stronger incentives to statistically discriminate at higher experience levels. Our estimates show that the effect of the increasing productivity of AFQT dominates the effect of learning in determining the coefficient on race early in the life cycle, with the effects roughly canceling out after five years.

Part of the reason why blacks earn less than whites can be explained by the fact that they accumulate less labor market experience than whites. We do not model discrimination in the hiring process directly, so our model cannot capture this source of inequality. In order to account for differences in actual experience, we include a cubic in actual experience in the estimation equation (6) and present the results in Figure 1 of the Web Appendix. As expected, the coefficient on *Black* does not start as negative, and does not fall as much as when we control for actual experience. The coefficients on *AFQT* and the learning parameter do not seem sensitive to controlling for actual experience. The true productivity of AFQT, however, starts out lower and peaks at about 0.19 as opposed to 0.24 in panel D of Figure 3. Even after controlling for actual experience our main results from Figure 3 remain; employers appear to statistically discriminate on the basis of race and learn about ability over time.

IV. Robustness Checks

The results so far suggest that AFQT is nearly perfectly revealed in the college market, but is only revealed over time in the high school market, and that, consistent with statistical discrimination, blacks only receive lower wages in the high school market. In this section, we check the robustness of the results along five dimensions. First, we investigate the sensitivity of the results to different assumptions regarding the determination of labor force participation. Second, we investigate whether the first four years of high school labor market experience play a similar role to college in revealing ability by seeing if our results change when we remove wage observations from the first four years after high school. If so, the differences between high school and college that we have documented might more accurately be characterized as age effects. Third, we show specifications that use father's education as a proxy for ability instead of the AFQT. Fourth, we include additional interaction or race and AFQT with year effects to see if time trends affect our results. Lastly, we check if patterns observed in the wage residual are consistent with our learning story.

A. Controlling for Selection

All of the results presented so far do not account for selection into the labor market. Differences in labor force participation by race can be very important when estimating log wage equations as shown in Richard Butler and James J. Heckman (1977) and Charles Brown (1984). In order to control for selection, we could model the decision to participate in the labor force and estimate a rich structural model of wage offers and labor market entry decisions. This, however, proves to be too complicated for the purpose of this paper. Instead, we follow Neal and Johnson (1996) by assigning an arbitrary wage to nonparticipants and estimate a median regression for the whole sample. If the wage offers that nonparticipants receive lie below the median wage offers participants receive, these median regressions allow us, in a crude way, to control for selection. This approach of controlling for some form of selection is not, in our opinion, rigorous enough to be used throughout the paper. This method does not deal well with the fact that potential experience overstates actual work experience or that experience is endogenous, including the possibility that employers may not hire workers whom they do not expect to be productive.

The results from these median regressions are presented in Table 5. These regression results mirror those presented earlier in the paper. Specification (1) estimates our baseline specification for the high school sample. The returns to AFQT are very small initially with a statistically insignificant coefficient of 0.018, but increase sharply in 10 years with a statistically and economically significant coefficient of 0.1395. Blacks earn about 12 percent less than whites, and this difference increases by an additional 4 percent in 10 years. The same patterns can be seen in specification (2) where we control for region of residence and part time status.

Specifications (3) and (4) repeat the same procedure for the college sample. The returns to AFQT in specification (3) are initially very large and significant with a coefficient of 0.1453, and these returns do not change much with experience. The

TABLE 5—THE EFFECTS OF AFQT ON LOG WAGES CONTROLLING FOR SELECTION

Model	High school		College		College minus HS	
	(1)	(2)	(3)	(4)	(5)	(6)
Standard. AFQT	0.0180 (0.0138)	0.0261** (0.0157)	0.1453** (0.0511)	0.1205** (0.0416)	0.007	0.020
AFQT \times exper/10	0.1395** (0.0212)	0.1262** (0.0194)	0.0162 (0.0668)	0.0485 (0.0559)	0.061	0.154
Black	−0.1196** (0.0302)	−0.1007** (0.0313)	0.0625 (0.0863)	0.0765 (0.0692)	0.024	0.023
Black \times exper/10	−0.0369 (0.0444)	−0.0459 (0.0418)	−0.0811 (0.0967)	−0.0887 (0.0922)	0.643	0.7741
Pseudo R^2	0.0464	0.0512	0.0850	0.0950		
Observations	13,134	13,108	4,176	4,176		
Additional controls	No	Yes	No	Yes	No	Yes

Experience measure: Years since left school for the first time < 13

Notes: We assign a zero log-wage to respondents who are not working at the time of the interview, and then estimate the log-wage equation using a median regression. All specifications control for urban residence, a cubic in experience, and year effects. Specifications (2) and (4) also control for region of residence and for part-time versus full-time jobs. In specification (5), we report the bias-adjusted bootstrapped p -values for the difference in the coefficients of specifications (1) and (3). Similarly, specification (6) compares (2) and (4). The standard errors reported are block-bootstrapped and control for clustering at the individual level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

coefficient on $AFQT \times \text{exper}/10$ is statistically insignificant with a magnitude of 0.0162. Similar patterns can be seen in the *Black* and $Black \times \text{exper}/10$ coefficients although their magnitude is smaller and they are not significant. Including additional controls in model (4) does not change the qualitative nature of the results.

In specifications (5) and (6) of Table 5, we test if the coefficients presented are significantly different in the college versus the high school market analogously to specifications (5) and (6) of Table 2. The results in specification (5) closely resemble those of Table 2 in that there are significant statistical and economical differences between the college and the high school samples in the $AFQT$, $AFQT \times \text{exper}/10$ and the *Black* coefficients. The findings are identical in specification (6) except for the slight statistical insignificance of the differences in the $AFQT \times \text{exper}/10$ coefficients.

B. College versus the First Four Years of Experience in the High School Market

When looking at the differences in the immediate returns to AFQT across the high school and college markets, one may be concerned that ability is actually revealed in the first four years after high school regardless of whether one attends college. If this is the case, the initial return to AFQT will be higher for college graduates than for high school graduates even if both college attendance and high school labor market experience reveal AFQT equally. In order to test this alternative explanation, we reestimate the regressions in Table 2, and for high school graduates, we exclude observations that come from the first four years in the labor market.

The results presented in specifications (1) of Table 6 are very similar to those of Table 2. The initial returns to AFQT are very low and insignificant at 0.0104,

TABLE 6—COLLEGE VERSUS FOUR YEARS OF EXPERIENCE AFTER HIGH SCHOOL

Model	High school		HS at exper=4 versus college <i>P</i> -values	
	(1)	(2)	(3)	(4)
Standard. AFQT	0.0104 (0.0200)	0.0109 (0.0199)	0.017	0.023
AFQT × exper/10	0.1201** (0.0230)	0.1126** (0.0226)	0.043	0.076
Black	−0.1026** (0.0414)	−0.0913** (0.0407)	0.001	0.001
Black × exper/10	0.0074 (0.0466)	0.0093 (0.0459)	0.099	0.097
<i>R</i> ²	0.1375	0.1642		
Observations	9,236	9,226		
Additional controls	No	Yes	No	Yes
Experience for HS grad: 4 years since left school < 13				

Notes: We exclude the first four years in the labor market for high school graduates. Specification (1) controls for urban residence, a cubic in experience and year effects. Specification (2) also controls for region of residence and for part-time versus full-time jobs. In specification (5), we report the *p*-values for the difference in coefficients between high school at four years of experience, and college. Specification (6) makes the same comparison by controlling for additional variables as in specification (2). The White/Huber standard errors in parenthesis control for correlation at the individual level.

**Significant at the 5 percent level.
*Significant at the 10 percent level.

and by 10 years, this return increases to 0.1201.²⁹ The same patterns can be seen in specification (2) where we include additional controls. In columns 3 and 4, we test whether the coefficients for high school graduates that have been in the market for four years are different from those of college graduates. As we can see from the *p*-values presented, all the coefficients are significantly different between the high school graduate (at experience = 4) and the college graduate samples. The results of Table 6 confirm that ability is revealed much later in the high school labor market than in the college market.

C. Father’s Education as a Measure of Ability

So far we have provided evidence that graduating from college reveals a single measure of ability AFQT. Here, we show that a similar pattern is found in the data for another correlate of ability that is difficult for employers to observe directly, father’s education. We estimate the log wage regressions including father’s education in Table 7. In all specifications, father’s education is divided by ten, so the coefficients should be interpreted as the return to a ten-year increase in father’s education.

Specification (1) shows that, for high school graduates, the effect of father’s education on log wages is initially small and statistically insignificant. Analogous to AFQT, the returns to father’s education increase significantly with experience, implying that

²⁹ Note that we do not change the experience variable implying that the minimum for the experience variable for high school graduates is five. Hence, the returns to AFQT at the minimum is the base return plus 0.5×0.1201 .

TABLE 7—THE EFFECTS OF AFQT AND FATHER'S EDUCATION ON LOG WAGES

	High school		College	
	(1)	(2)	(3)	(4)
Model:				
Black	−0.0495* (0.0270)	−0.0537* (0.0305)	0.0339 (0.0559)	0.1298** (0.0596)
Father's education/10	0.0361 (0.0386)	0.0392 (0.0402)	0.0819 (0.0648)	0.0575 (0.0646)
Standardized AFQT		−0.0042 (0.0150)		0.1395** (0.0375)
Black × experience/10	−0.1568** (0.0355)	−0.0241 (0.0402)	−0.1497** (0.0668)	−0.1448** (0.0727)
F. Educ/10 × experience/10	0.1480** (0.0538)	0.0780 (0.0530)	−0.0219 (0.0978)	−0.0370 (0.0995)
AFQT × experience/10		0.1357** (0.0201)		0.0271 (0.0501)
R^2	0.1345	0.1630	0.1446	0.1729
Observations	10,034	10,034	3,983	3,983

Experience measure: Years since left school for the first time

Notes: All specifications control for urban residence, a cubic in experience, and year effects. Potential experience is limited to less than 10 and 13 years for the high school and the college sample, respectively. The White/Huber standard errors in parenthesis control for correlation at the individual level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

10 additional years of father's education yields a 15 percent increase in wages 10 years after high school. In specification (2), where we also include *AFQT* and its interaction with experience, both *AFQT* and father's education have small and insignificant intercepts. Although the inclusion of *AFQT* decreases the magnitude and significance of the coefficients on father's education interaction with experience, this coefficient is still about four times the magnitude of the father's education base coefficient.

We now turn to specification (3), which analyzes the effect of father's education on wages for college graduates. The coefficient on father's education is still statistically insignificant, but its magnitude is quite sizable. The point estimate implies an 8 percent increase in earnings from a 10 year increase in father's education. If we compare this to the analogous coefficient in specification (1), we can see that the returns to father's education are initially higher for college graduates than for high school graduates. The coefficient on father's education times experience is negative, small, and insignificant. This last coefficient was large and significant for high school graduates. Similar results hold even after we include *AFQT*, although this decreases the immediate returns to father's education in the college market.

Taken together, although not statistically significant in all cases, the results for father's education are consistent with our main hypothesis that the ability of high school graduates is revealed gradually, while the ability of college graduates is more or less revealed directly upon entry into the labor market.³⁰

³⁰ We also investigated whether similar patterns held for father's education in the PSID. Although not statistically significant, the qualitative findings matched those of Table 7.

TABLE 8—CONTROLLING FOR TIME CHANGING EFFECTS OF EDUCATION, RACE, AND AFQT

	(1)			(2)		
	High school	College	Diff. <i>P</i> -value	High school	College	Diff. <i>P</i> -value
Standard. AFQT	0.0180 (0.0190)	0.1227** (0.0418)	0.003	0.0210 (0.0204)	0.1177** (0.0430)	0.006
AFQT × exper/10	0.1048** (0.0378)	0.0134 (0.0609)	0.106	0.0935** (0.0435)	0.0066 (0.0645)	0.128
Black	−0.0618** (0.0267)	0.1097* (0.0563)	0.006	−0.1511** (0.0702)	0.1005 (0.0796)	0.031
Black × exper/10	−0.0370 (0.0350)	−0.1315* (0.0693)	0.223	−0.0779 (0.0767)	−0.1563 (0.0989)	0.359
AFQT × year F.E.	Yes			Yes*		
Black × year F.E.	No			Yes**		
<i>R</i> ²	0.3059			0.3065		
Observations	15,907			15,907		

Experience measure: Years since left school for the first time < 13

Notes: For each specification, we pool the data and estimate a model interacted with education fixed effects. Included but not shown in the table are education interactions with a cubic in experience, urban residence, and with year effects. Specification (1) controls for the interaction AFQT × year fixed effects and specification (2) adds Black × year fixed effects. Both these interactions are not allowed to vary with education. The AFQT and Black coefficients are presented for the base year 1979. The White/Huber standard errors in parenthesis control for correlation at the individual level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

D. Controlling for Time Trends in Returns to Ability and in Racial Discrimination

The NLSY79 sample we use contains mostly a single cohort of workers, so there could be concerns that our results reflect time trends in returns to ability and racial discrimination rather than experience effects. In order to address these concerns we include *AFQT*-by-year fixed effects and race-by-year fixed effects interactions to our baseline specifications. We pool all the data for college and high school graduates and interact everything with education dummies except for the *AFQT*-by-year fixed effects and race-by-year fixed effects which are held constant across education groups. The results from this procedure are presented in Table 8.

In specification (1) of Table 8, we include *AFQT*-by-year fixed effects interactions. The results are very similar to those presented in Table 2. The returns to AFQT are higher for college graduates than for high school graduates, and these returns increase faster for high school graduates than for college graduates, although this difference is slightly statistically insignificant. The coefficient on *Black* and *Black* times potential experience are also very similar to those in Table 2. In specification (2), we add black-by-year fixed effects and find that results with respect to AFQT remain unchanged. The coefficient on black is initially more negative and it decreases faster with experience although it is not statistically different from our previous results. To summarize, we find that time trends in returns to ability and in racial discrimination do not affect our findings.

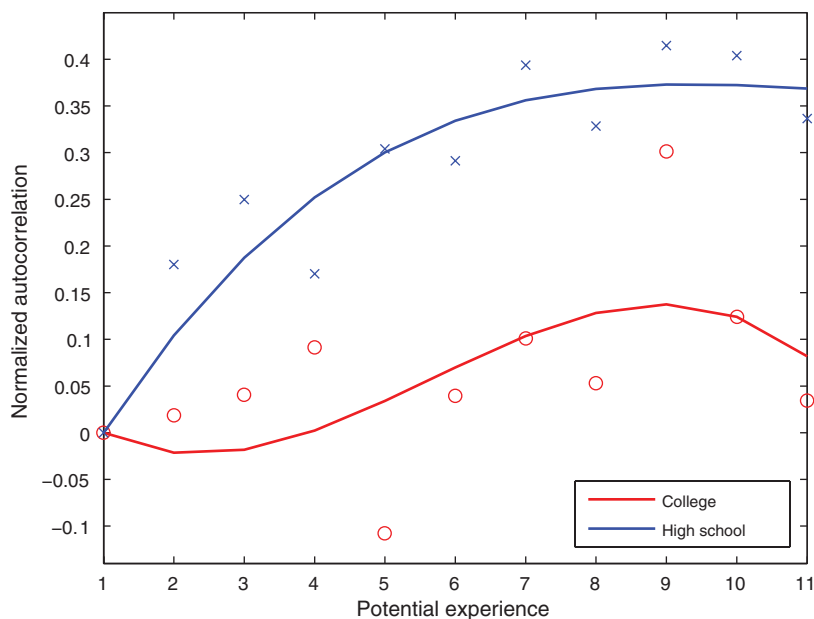


FIGURE 4. THE EVOLUTION OF THE WAGE RESIDUAL AUTOCORRELATION OVER POTENTIAL EXPERIENCE

Notes: The wage residual is constructed by estimating the wage equation (6) separately for each experience level. We normalize the residual autocorrelations by its initial level and fit a cubic in potential experience to it.

E. Analysis of the Wage Residual

If learning is occurring more in the high school market than in the college market, this may be true of abilities not captured by AFQT. If employers are learning about these other abilities, the autocorrelation in the wage regression residual should be increasing with experience until employers have learned everything they need to know. If our learning hypothesis is true, the autocorrelation in the wage residual should be increasing faster for high school graduates, where learning is important, than for college graduates where most of the learning has already taken place.

Figure 4 plots the autocorrelations of the wage residual normalized to zero in the first year of experience. The residual is constructed by estimating the wage equation (6) separately for each experience level. Using these residuals, we calculate the one year autocorrelations at the individual level. We normalize the estimated autocorrelation by its level in the first year of experience and fit a cubic in experience to it. The results confirm that the autocorrelation increases faster for the high school sample than for the college sample.³¹ This finding is consistent with our learning story, although our hypothesis may not be the only driver of the observed patterns.

If learning is important, the weight put on ability should increase over time, and this will increase the variance of the observed wages in the population, since wages

³¹ Because of the low number of individuals that have wage observations for two consecutive years, we cannot draw strong conclusions in terms of statistical significance.

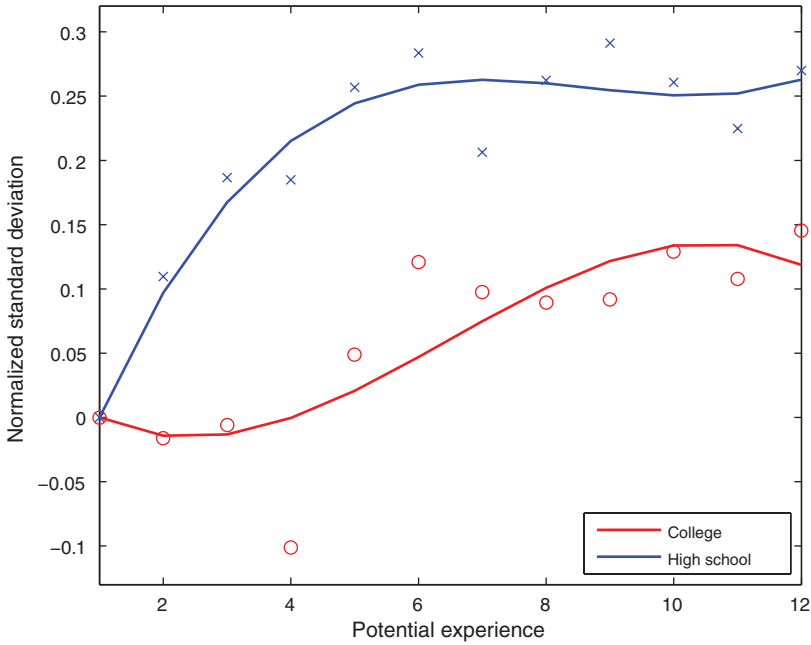


FIGURE 5. THE EVOLUTION OF THE WAGE RESIDUAL STANDARD DEVIATION OVER POTENTIAL EXPERIENCE

Notes: The wage residual is constructed by estimating the wage equation (6) separately for each experience level. We normalize the residual standard deviation by its initial level and fit a cubic in potential experience to it.

should reflect ability more with experience. We investigate whether the standard deviation of the wage residual grows faster for high school graduates than for college graduates as our hypothesis would predict. Figure 5 plots the wage residual standard deviation normalized by its initial level and fits a cubic to it. Consistent with our learning story, the standard deviation seems to increase faster for the high school sample than for college graduates.³²

V. Conclusion

The main argument in this paper is that education plays more than just a signaling role in the determination of wages. Specifically, we argue that graduation from college allows individuals to directly reveal their ability to potential employers. Using data from the NLSY, we show that the returns to AFQT, our measure of ability, are large for college graduates immediately upon entering the labor market, and do not change significantly with labor market experience. In contrast, returns to AFQT for high school graduates are initially very close to zero, and rise steeply with experience. These results suggest that ability is observed perfectly for college graduates, but is revealed to the labor market more gradually for high school graduates.

³² These differences are statistically significant from zero.

Consistent with the notion that ability is nearly perfectly revealed, we find that, if anything, blacks earn more than whites in the college market. The lack of evidence of statistical discrimination in the college market is especially noteworthy given the large difference in the AFQT distribution for college-educated blacks and whites. On the other hand, we provide evidence that blacks earn 6 percent less than whites initially, and this gap increases with labor market experience in the high school market. We argue that this wage difference in the high school market may arise solely due to statistical discrimination given the information problem that potential employers face. Estimates of a model of employer learning and statistical discrimination are consistent with this explanation.

The combination of discrimination against blacks in the high school market and perfect revelation of ability in the college market is also consistent with the fact that, conditional on AFQT, blacks are more likely to earn a college degree than whites. Facing discrimination in the high school market, blacks on the college-high school margin have a stronger incentive to reveal their ability directly by attending college.

The amount of statistical discrimination that black workers face after high school may be reduced by devising some channel that allows blacks to better signal their ability to the market. One way to bridge the informational gap between workers and employers would be administering some form of an exit examination for high school graduates. Arguments for exit exams have been made before, and there is some literature that analyzes and argues for such tests on the grounds that they provide a way for individuals to reveal ability to the labor market. See, for example, John H. Bishop (2006), Bishop (2005), and Bishop and Ferran Mane (2001). Exit exams would give employers a clearer signal of workers ability and would reduce their incentives to statistically discriminate.

MATHEMATICAL APPENDIX

Here, we present a model of statistical discrimination that we estimate in Section IV. Much of this model is based on the standard employer learning model formalized by Farber and Gibbons (1996). A model closely related to ours was formulated by Lange (2007), who estimates the speed of employer learning, assuming symmetrical learning and a competitive labor market. We maintain these crucial assumptions in our specification.³³

We specify the true log-productivity of a worker as

$$(9) \quad \chi_{i,x} = f(s_i) + \lambda_x(z_i + \eta_i + q_i) + \tilde{H}(x).$$

The function $f(s_i)$ captures the effect of schooling on productivity for individual i . The variable q_i represents the information about the ability of the worker that is

³³ Whether or not employers have private information about workers is an open question in the literature. Our assumption is supported by findings in Uta Schönberg (2007) who reports that for white high school graduates learning appears to be symmetric, meaning firms do not have any private information. Since we don't find evidence of racial differences in the returns to AFQT, learning should be symmetric for high school graduate blacks too.

observed by the employers, but that is not available to the researcher. On the other hand, z_i is a measure of ability observed by the researcher, but not the employers. In our case, this variable is the AFQT score. The part of productivity that is unobserved by both the employer and the researcher is given by η_i . The effect of (z, q, η) on log-productivity is captured by the parameter λ_x .³⁴ Finally, $\tilde{H}(x)$ denotes a function that captures experience effects on log-productivity. This function is assumed to be independent of education and ability measure z_i . This means that employers focus on predicting productivity based on variables s_i , q_i , and signals they get over time.

The first important assumption we make is that $z_i \perp \eta_i, q_i$. This means that the unobserved part of ability and the information that employers have initially cannot be used to predict z_i . The assumption that $z_i \perp \eta_i$ is innocuous, and there is some evidence that $z_i \perp q_i$ in the data.³⁵ We suppress the subscript i for ease of notation from now on.

Also assume (z, s, q, η) are jointly normally distributed. This means that the expectation of $\eta | (s, q)$ is linear in (s, q) :

$$(10) \quad \eta = \alpha_1 s + \alpha_1 q + v.$$

Although employers do not observe z , we assume they observe the average ability of the group the worker belongs to $\bar{z} = E(z | s, x, \text{race})$. Specifically, in our case employers know the average AFQT for each race. Employers then predict z by the linear relation:

$$(11) \quad z = \bar{z} + e.$$

Substituting equation (11) in (9), we can write the initial log-productivity at $x = 0$ as

$$(12) \quad \begin{aligned} \chi &= rs + \lambda_0(\bar{z} + e + \eta + q) + \tilde{H}(0) \\ &= E(\chi | \bar{z}, q) + \lambda_0(e + \eta). \end{aligned}$$

So, $\lambda_0(e + \eta)$ is the expectation error employers have initially. Over time, as they observe job performance and learn about χ , this expectation error decreases. More specifically, every period x employers get a signal given by

$$(13) \quad y_x = z + \eta + \varepsilon_x,$$

where ε_x is independently and normally distributed with a time dependent variance $\sigma_{\varepsilon, x}^2$. We maintain that ε_x is orthogonal to all other variables in the model.

³⁴ The lack of separate coefficients for z , η , q is without loss of generality since we can define η and q such that their coefficients are the same as that of z .

³⁵ In all the specifications of Table 2 and Table 5, the coefficients on AFQT are almost zero and not statistically significant for high school graduates. Assuming that AFQT matters for productivity initially, this can be interpreted as evidence that the information employers have initially cannot be used to predict AFQT.

Similar to Lange (2007), the normality assumptions make the structure of employer learning very simple. In the initial period, when $x = 0$, the mean of the prior of employers' beliefs about $(z + \eta)$ is

$$(14) \quad \mu_0 = \bar{z} + \alpha_1 s + \alpha_1 q.$$

At some period $x > 0$, the employers get a signal y_x , and they update their beliefs. Because of the normality assumption, the mean of the posterior is

$$(15) \quad \mu_x = (1 - \theta_x)\mu_{x-1} + \theta_x y_x,$$

where θ_x is some optimal Bayesian weight that the employers put on the prior mean. This process continues for any amount of experience as long as the worker's performance is observed by the employers.

At time x , employers would expect the productivity of a worker to be

$$(16) \quad E_x(\chi | \bar{z}, q, s, Y^x) = rs + \lambda_x q + \lambda_x [(1 - \theta_x)\mu_{x-1} + \theta_x y_x] + \tilde{H}(x),$$

where $Y^x = \{y_1, \dots, y_x\}$. As employers learn more and more, the term $[(1 - \theta_x)\mu_{x-1} + \theta_x y_x]$ converges to $(z + \eta + q)$, so their expectation error collapses to zero.

Similar to the standard employer learning literature, we will maintain the assumption that all employers have access to the same information, and that labor markets are competitive. Wages are then set equal to the expected productivity of a worker:

$$(17) \quad W_x = E_x[\exp(\chi) | \bar{z}, q, s, Y^x].$$

The normality assumptions above imply that the distribution of χ conditional on (s, q, Y^x) is normal. We can then write log wages as³⁶

$$(18) \quad w_x = \lambda_x [(1 - \theta_x)\mu_{x-1} + \theta_x y_x] + C_x,$$

where

$$C_x = rs + \lambda_x q + \tilde{H}(x) + \frac{\sigma_x^2}{2}.$$

Equation (18) gives the wages paid to a worker given (\bar{z}, q, s, Y^x) . We cannot observe q and Y^x , so, in order to be able to estimate the wage equation, we need to express log wages as a function of what we observe or (\bar{z}, z, s, x) . The first step to doing this is to define a linear projection of (q, η) :

$$(19) \quad \begin{aligned} q &= \gamma_1 s + u_1 \\ \eta &= \gamma_2 s + u_1. \end{aligned}$$

³⁶ Using properties of a lognormal distribution, $E[\exp(\chi) | \bar{z}, q, s, Y^x] = \exp(E[\chi | \bar{z}, q, s, Y^x] + \sigma_x^2/2)$. The expectation error is independent of $(\bar{z}, q, s, Y^x, \eta)$, so $\sigma_x^2/2$ does not vary with (\bar{z}, q, s, η) .

This allows us to determine log wages as a function of only (\bar{z}, z, s, x) . This linear projection is given by³⁷

$$(20) \quad E^*(w_x|z, s) = \lambda_x[(1 - \theta_x)E^*(\mu_{x-1}|z, s) + \theta_x E^*(y_x|z, s)] + c_x,$$

where

$$c_x = rs + \lambda_x(\gamma_1 s + u_1) + \tilde{H}(x) + \frac{\sigma_x^2}{2}.$$

Substituting in equation (20) for μ_x as given in equation (15), and for q given in equation (19), we can write log wages at $x = 1$ as

$$(21) \quad w_1 = \lambda_1[(1 - \theta_1)\bar{z} + \theta_1 z] + k_1,$$

where

$$k_1 = \lambda_1(1 - \theta_1)[\alpha_1 s + \alpha_1(\gamma_1 s + u_1)] + c_1.$$

Log wages at period $x = 1$ is a weighted average of the mean group AFQT and of the AFQT score plus a constant. The constant k_1 reflects that employers prior depends not only on mean ability \bar{z} , but also on schooling s and information available only to employers q .

Repeating this procedure for some $x > 1$, we can express log wages as

$$(22) \quad w_x = \lambda_x \left\{ \prod_{i=1}^x (1 - \theta_i) \bar{z} + \left[1 - \prod_{i=1}^x (1 - \theta_i) \right] z \right\} + k_x,$$

where

$$k_x = \lambda_x \prod_{i=1}^x (1 - \theta_i) [\alpha_1 s + \alpha_1(\gamma_1 s + u_1)] + c_x.$$

In order to give the log-wage equation a form similar to that shown in Lange (2007), we can rewrite it as

$$(23) \quad w_x = \lambda_x \{ (1 - \Theta_x) \bar{z} + \Theta_x z \} + k_x,$$

which is our estimating equation in Section IV. Note that as experience increases, the weight on \bar{z} goes to zero and the weight on z goes to one since, as long as employers are getting new signals every period, $\prod_{i=1}^x (1 - \theta_i) \rightarrow 0$.

³⁷ Here, $E^*(X|Y)$ denotes the linear projection of X on Y .

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