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BEYOND SIGNALING AND HUMAN CAPITAL: EDUCATION AND THE REVELATION OF ABILITY

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ABSTRACT

In traditional signaling models, education provides a way for individuals to sort themselves by ability. Employers in turn use education to statistically discriminate, paying wages that reflect the average productivity of workers with the same given level of education. In this paper, we provide evidence that education (specifically, attending college) plays a much more direct role in revealing ability to the labor market. We use the NLSY79 to examine returns to ability early in careers; our results suggest that ability is observed nearly perfectly for college graduates but is revealed to the labor market much more gradually for high school graduates. As a result, from very beginning of the career, college graduates are paid in accordance with their own ability, while the wages of high school graduates are initially completely 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 the returns to ability. In particular, we find no racial differences in wages or returns to ability in the college labor market, but a 6-10 percent wage penalty for blacks (conditional on ability) in the high school market. These results are consistent with the notion that employers use race to statistically discriminate in the high school market but have no need to do so in the college market. That blacks face a wage penalty in the high school but not the college labor market also helps to explains why, conditional on ability, blacks are more likely to earn a college degree, a fact that has been documented in the literature but for which a full explanation has yet to emerge.

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1 Introduction

In traditional models of ability signaling [Spence 1973, Weiss 1995], education provides a way for individuals to sort into groups (education levels) that are correlated with ability. Employers in turn 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, Farber and Gibbons (1996) and Altonji and 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 10-12 years of an individual's career.[1] Specifically, 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 with labor market experience. In contrast, returns to AFQT for high school graduates are initially very close to zero and rise steeply with experience. We also observe similar patterns for another proxy for ability, father's education. 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. Our general conclusion is that from the very beginning of the career, college graduates are paid in accordance with their own ability, while individual ability is revealed to market (and reflected in wages) much 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,

[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 Neal (2004) to deal with selection reveal similar patterns to those for males.

majors, standardized test scores and, perhaps even more importantly, the college attended.[2] In this way, our analysis certainly 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 labor 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 perfectly revealed, we find no differences in wages or the returns to ability across race.[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] By contrast, we estimate that blacks earn 6-10 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 on the evolution of racial wage differences also provide a coherent explanation for the fact that, conditional on ability, blacks obtain more education than whites (Neal and Johnson (1996), Lang and Manove (2006)). 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 stronger incentives to obtain a college degree than whites with comparable AFQT scores. Our analysis also rules out other potential explanations for the greater level of educational attainment of blacks. One such explanation that has been put forth in the literature is that employers have more difficulty assessing the ability of blacks versus whites.[6] In fact, we find no

[2] In the analysis presented below, we show that this type of information explains a large portion of the variation in AFQT scores and father's education.

[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, Fang (2006), Altonji and Pierret (1998), Lange (2007), Ashenfelter and Krueger (1994), Weiss (1995), Lang (1994), Stiglitz (1975), Mincer (1974) and Becker (1964). Our analysis also naturally suggests a reinterpretation of the findings of the employer learning literature following Altonji and Pierret (2001).

[4] If anything, blacks with especially high AFQT scores appear to earn a premium upon graduating from college.

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

[6] This is a key potential explanation explored in Lang and Manove (2006). Using a different argument, they also reject this explanation. More generally, asymmetric employer learning due to race and differences between incumbent and outside firms is explored in work of Schonberg (2007), Pinkston (2006), Zhang (2006), DeVaro and

difference in the initial level or speed of employer learning for blacks and whites in both the high school and college labor markets. Taken as a whole, our results imply that (college) education plays a significant role in directly revealing ability and that this mechanism provides a coherent explanation the observed racial differences in both wages and educational attainment.

The rest of the paper is organized as follows. Section 2 gives a general overview of the data we use for our empirical analysis. Section 3 presents our main empirical findings, which consist of a series of wage regressions. To fully interpret these findings, Section 4 uses the resulting coefficients to estimate a simple model of employer learning and statistical discrimination. Section 5 presents some additional specifications of our main estimating equations and Section 6 concludes.

2 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 years 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 CPS[8] section of the NSLY.[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

Waldman (2004), Bernhardt (1995), Gibbons and Katz (1991), Greenwald (1986), and Waldman (1984).

[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 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 one dollar and less than one hundred dollars per hour.

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 thirteen years for the high school sample, and less than ten years for the college sample. The reason for this, as explained in the appendix that replicates AP, is that there exists a nonlinear 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 thirteen years and less than ten years for the high school and the college samples, respectively. Another reason for this sample selection is attrition in the NLSY79, which implies that the number of observations falls noticeably with experience. We also exclude from our analysis observations that correspond to the same year that individuals responded that they left school. There were few such observations and they were dropped because they were very noisy and are reported during the transition period to the job market. A more detailed explanation of the sample construction is given in the 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 we show below, 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 in the college labor market later in the

[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 we discuss later in the paper, using the sampling weights had no effect on the qualitative resuls.

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

Table 1: Summary Statistics for College and High School Graduates by Race

	Blacks			Whites		
	Total	HS Grad	Col Grad	Total	HS Grad	Col Grad
Observations†	7,177	6,122	1,055	16,548	12,049	4,499
AFQT						
Mean	-.664	-.840	.359	.483	.252	1.102
Std. Dev.	.878	.769	.762	.806	.785	.460
Urban Residence (%)	83.38	81.82	92.48	72.60	68.71	83.02
Region (%)						
Northeast	14.77	15.21	12.23	21.34	20.18	24.45
North Central	15.68	14.79	20.85	35.59	36.68	32.68
South	62.51	63.99	53.93	28.37	28.13	28.99
West	7.04	6.01	12.99	14.70	15.01	13.88
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
Actual Experience						
Cum. Weeks Worked/52						
Ages <25	2.40	2.44	1.66	2.73	2.86	1.81
Ages 25-30	5.50	5.72	4.46	5.96	6.58	4.71
Ages 30-35	8.71	8.68	8.86	9.56	9.70	9.27
Ages >35	12.15	11.99	12.9811	13.53	13.21	14.20
Potential Experience						
Years Since Left School						
Ages <25	3.36	3.45	1.74	3.29	3.51	1.54
Ages 25-30	7.66	8.27	4.67	7.16	8.40	4.56
Ages 30-35	12.36	12.95	9.69	11.89	13.20	9.30
Ages >35	17.43	18.02	14.44	17.04	18.23	14.58

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

paper.

3 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 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) (AP thereafter) and Farber and Gibbons (1996). We replicate the main results of AP using our sample and present their results in the appendix.

In this paper we argue that education is more than a tool for workers to signal their ability. Our hypothesis is two-fold: (i) that employers learn slowly about the ability of high school graduates and (ii) 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, Bauer and Haisken-DeNew (2001), Farber and Gibbons (1996), 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 wages equation is:

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

Log wages w_i of individual 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.[13]

3.1 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 for 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 ten 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 13% 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.[14]

[13] In additional specifications not reported in the paper we added a complete set of year-education and year-AFQT interactions. Adding these additional controls had no effect on the qualitative nature or statistical significance of the key results presented below.

[14] 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 4 below, where we develop a model of employer learning and statistical discrimination.

Table 2: The Effects of AFQT on Log Wages for High School and College Graduates

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Standardized AFQT	.0060	.0078	.1467**	.1403**
	(.0130)	(.0129)	(.0364)	(.0369)
AFQT x experience/10	.1265**	.1187**	.0179	.0281
	(.0176)	(.0173)	(.0611)	(.0608)
Black	-.0628*	-.0483	.0922	.0867
	(.0267)	(.0259)	(.0575)	(.0563)
Black x experience/10	-.0369	-.0398	-.0823	-.0681
	(.0350)	(.0345)	(.0959)	(.0961)
R^2	0.1628	0.1871	0.1553	0.1688
Additional variables	No	Yes	No	Yes
No. Observations	11798	11775	3373	3373
Experience measure: Years since left school for the first time				

Note - Specifications (1) and (3) 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 vs full time jobs. There are fewer observations in specification (2) versus specification (1) because some observations are missing region of residence and/or full/part time status. Potential experience is restricted to less than thirteen and ten years for the high school and the college market, respectively. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

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 is small and not statistically. 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 a 15 percent increase in wages. Moreover, the returns to AFQT are only slightly affected by experience, rising to only 16-17 percent 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.[15]

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. In Table 10 in the appendix, we report results for regressions of AFQT on SAT, PSAT, ACT and college major. The high R^2, ranging from 0.567 to 0.733 depending on the specification, of these regressions, which include variables describing only some of the information contained on a typical resume, indicate that this dimension of ability may be essentially revealed at the time of initial entry into the labor market. A more detailed discussion of these regressions can be found in the appendix.

3.2 Racial Differences

3.2.1 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.[16] Indeed, the median AFQT score for blacks who graduate from college 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

[15] While AFQT represents only a single dimension of ability, in Section 5 below, we report results that reveal a remarkably similar pattern for an alternative correlate of ability - father's education

[16] Similar findings about achievement tests gaps are documented earlier in the literature; see Neal (2006) for a detailed discussion.

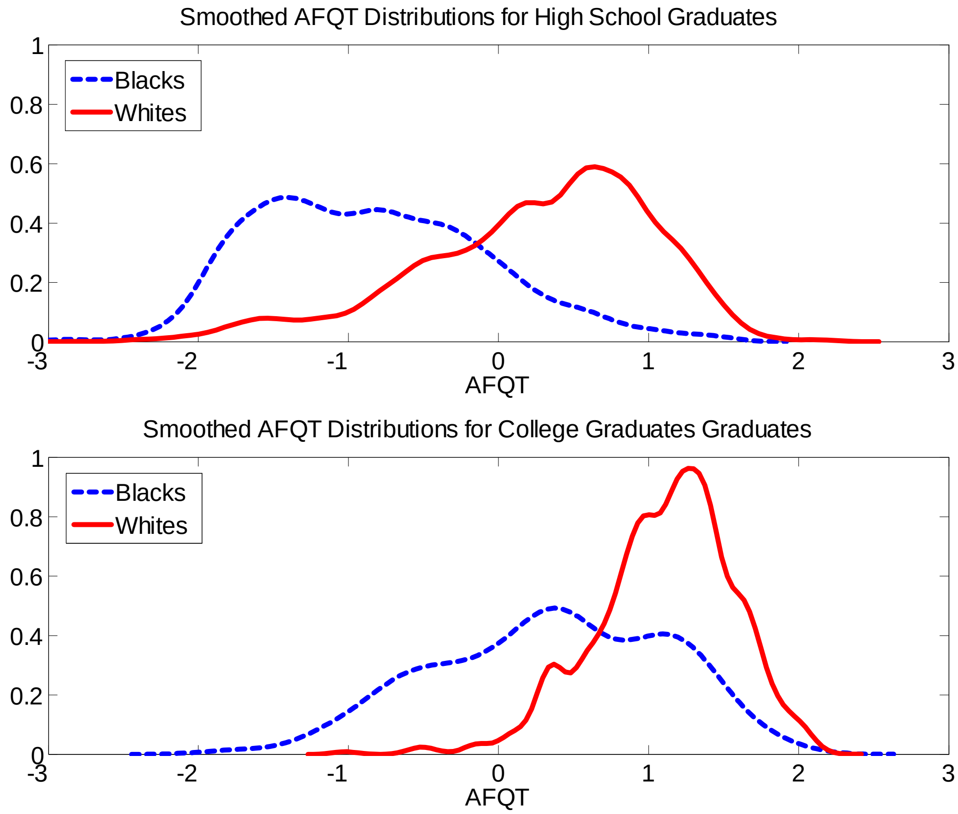

Figure 1: AFQT Distributions by Race and Education

basis of race.

Given the results for employer learning discussed in the previous subsection, 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 ten years of experience, conditional on AFQT, is 10 percent.[17]

[17] 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, Altonji and Pierret (2001)). These models would predict that employers should weight race less as they learn more directly about worker productivity. In the next section 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

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 nine percent higher wages than their white counterparts upon initial entry into the labor market. This premium declines to zero after about 11 years of labor market experience, although neither of these coefficients is statistically significant.[18]

The initial wage premium for college-educated blacks measured in the NLSY79 sample is driven by the especially high wages of a small number of blacks in the top decile of the AFQT distribution. In particular, Table 3 shows that the premium in specification (1) declines to zero when blacks in the top ten percent of the AFQT distribution are dropped from the sample in specifications (3). The results reported in Table 3 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.

Although the above-average labor market returns for high-AFQT blacks measured in the NLSY79 are statistically insignificant, 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.

3.2.2 Differences in Return to AFQT

Tables 4 reports the results of specifications that include interactions of race and AFQT. These specifications allow us to examine whether the initial level and speed of employer learning differs for blacks and whites in the high school and college samples.

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

[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 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.

Table 3: Explaining the Black College Premium in Wages

	Full College Sample		Limited College Sample	
	(1)	(2)	(3)	(4)
Model:				
Black	.0922	.0867	.0238	.0115
	(.0575)	(.0563)	(.0550)	(.0540)
Standardized AFQT	.1467**	.1403**	.1148**	.1041**
	(.0364)	(.0369)	(.0364)	(.0370)
AFQT x experience/10	.0179	.0281	.0554	.0721
	(.0611)	(.0608)	(.0628)	(.0625)
Black x experience/10	-.0823	-.0681	-.0045	.0223
	(.0959)	(.0961)	(.0980)	(.0987)
R^2	0.1553	0.1688	0.1560	0.1689
Additional Variables	No	Yes	No	Yes
No. Observations	3373	3373	3318	3318
Experience measure: Years since left school for the first time < 10				

Note - Specifications (1) and (2) use the full college sample, while specifications (3) and (4) exclude blacks at the top ten percent of the AFQT distribution. Specifications (1) and (3) 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 vs full time jobs. Potential experience is restricted to less than thirteen and ten years for the high school and the college markets, respectively. White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

Table 4: Racial Differences in the Effect of AFQT on Log Wages

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.0600*	-.0457	.0169	.0115
	(.0294)	(.0277)	(.1108)	(.0681)
Standardized AFQT	.0046	.0065	.1115*	.1040*
	(.0158)	(.0158)	(.0451)	(.0453)
Black x AFQT	-.0054	-.0052	.0143	-.0000
	(.0272)	(.0258)	(.0732)	(.0727)
AFQT x experience/10	.1246**	.1169**	.0633	.0743
	(.0217)	(.0213)	(.0766)	(.0762)
Black x experience/10	-.0335	-.0380	.0093	.0259
	(.0385)	(.0370)	(.1161)	(.1163)
Black x AFQT x exper/10	.0048	.0045	-.0283	-.0073
	(.0372)	(.0364)	(.1277)	(.1287)
R^2	0.1607	0.1871	0.1560	0.1690
Additional variables	No	Yes	No	Yes
No. Observations	11798	11775	3318	3318
Experience measure: Years since left school for the first time				

Note - Specifications (1) and (3) 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 vs full time jobs. Potential experience is restricted to less than thirteen and ten years for the high school and the college market. The college sample excludes blacks at the top tenth percentile of the AFQT distribution. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

Specifications (1) and (2) show results for the high school sample. The coefficient on black interacted with AFQT and black interacted with AFQT and experience are statistically and economically insignificant. These estimates imply that the process of employer learning is roughly the same for blacks and whites in the high school market.

As reported in specifications (3) and (4) of Table 4, when blacks in the top ten percent of the black AFQT distribution are dropped from the sample, the coefficients on the terms that interact race with AFQT are essentially zero. Taken together, these results lead to the strong conclusion that, except for the high end of the AFQT distribution where college educated blacks seem to earn a sizable, albeit statistically insignificant, premium, there are no significant difference in returns to AFQT between whites and blacks in either the high school or college samples.

3.3 Explaining racial differences in education attainment

Lang and Manove (2006) (LM, hereafter) 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 should also imply that, conditional only on AFQT, blacks should earn more than whites.[21]

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,

[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 both 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) shows that, conditional on only AFQT, the racial wage gap is smaller but blacks continue to earn less than otherwise identical whites.

blacks obtain more education.[22]

4 Statistical Discrimination

We argue that our results for the high school sample can be reconciled with statistical discrimination on the basis of race. 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. 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 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 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.[23]

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

[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 the same as 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. In this way, it is possible for whites to earn more than blacks with the same AFQT score, provided the increased college attendance of blacks is not enough to offset the wage penalty that blacks face in the high school market.

[23] 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.

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 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: (i) employers learn about the individual's ability and (ii) 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 appendix we show that, under certain assumptions regarding the nature of learning and what employers initially know, log wages follow:

$$w_x = \lambda_x \left\{(1 - \Theta_x)\overline{AFQT} + \Theta_x AFQT\right\} + k_x \tag{2}$$

where k_x and 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 initially employers 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 the productivity of the worker, the weight will gradually be shifted from the group mean to the individual's ability.[24] We show in the appendix that as experience increases $\Theta_x \to 1$. 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

[24] Similarly, employers distribute some weight on education intitially, which dicreases 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 interesed in statistical discrimination on the basis of race and not education.

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 $\overline{AFQT}$ 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 $\lambda_x/(1-\Theta_x) > 1$, 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 can estimate equation (2) directly by regressing log wages on mean AFQT for each race and AFQT interacted with a full set of experience dummies similar to Lange (2007):

$$w_{i,x} = \beta_{x,\overline{AFQT}}\overline{AFQT}_{race} + \beta_{x,AFQT}AFQT \cdot + \beta'_{\Phi}\Phi_{i,t} + \beta_x + \varepsilon_x \tag{3}$$

To capture the effects of education and of the variables that only employers observe denoted by k_x in equation (2), we include experience dummies directly in the regression so this effect will be captured by β_x.We also control for demographics which are denoted as $\Phi_{i,t}$.

We can rewrite (3) as a function of a 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:

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

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

$$\beta^*_x = \beta_x + \beta_{x,\overline{AFQT}}\overline{AFQT}_{white}$$

we can write our estimating equation as:

$$w_{i,x} = \beta_{x,Black}Black + \beta_{x,AFQT}AFQT + \beta'_{\Phi}\Phi_{i,t} + \beta^*_x + \varepsilon_x \tag{4}$$

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 $\beta_{x,\overline{AFQT}_{race}} = \beta_{x,Black}/\left(\overline{AFQT}_{black} - \overline{AFQT}_{white}\right)$.

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 (4) we can then solve for λ_x and Θ_x:

$$\lambda_x = \beta_{x,AFQT} - 1.0922\beta_{x,Black} \tag{5}$$

$$\Theta_x = \frac{\beta_{x,AFQT}}{\beta_{x,AFQT} - 1.0922\beta_{x,Black}} \tag{6}$$

The results from the described estimation procedure are presented in Figure 2. The first two plots display the estimated coefficients on Black and AFQT for each experience level. We smooth the way these coefficients evolve with experience by fitting a cubic in experience. After the smoothing, the initial racial difference in wages is about 6% and in increases to 10% in about 12 years. The effect of a one standard deviation increase in AFQT starts at zero initially and increase to about 15% after 12 years of experience. These results are very similar to those previously shown in Table 2.

We use these smoothed experience profiles to calculate how much of the changes in the returns to race and AFQT can be attributed to employer learning, and how much to changes in the true productive value of AFQT. Sub-figures 2 and 3 of figure 2 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 at zero and by 12 years increases to 0.6, which means employers observe 60% of AFQT in about 12 years. The model is estimated separately for each year of experience. Thus the fact that learning is monotonically increasing in experience, provides some additional support for the model. The true productivity of AFQT is also increasing with experience. A one standard deviation increase in AFQT leads to a 7% increase in productivity initially which increases to about 22.5% 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 workers' productivities 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 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

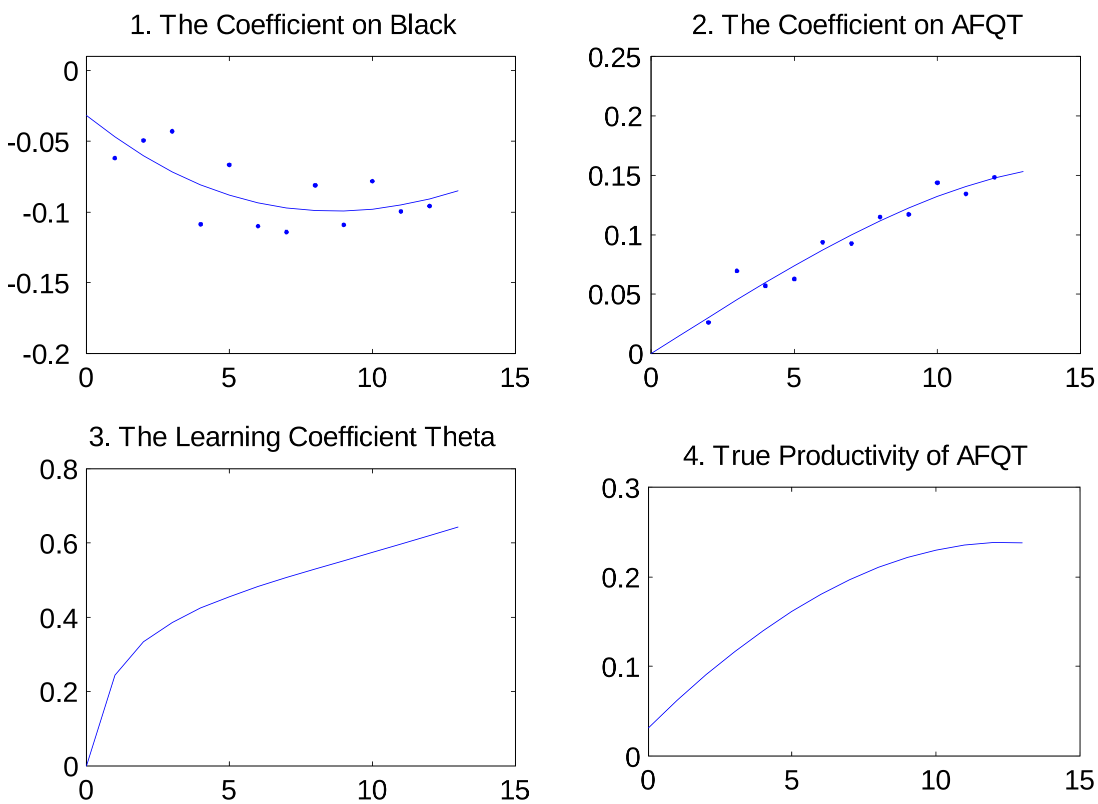

Figure 2: Plots 1 and 2 show the estimated coefficients $\beta_{x,Black}$ and $\beta_{x,AFQT}$. The estimates for $\beta_{x,AFQT}$ and $\beta_{x,Black}$ are smoothed using a cubic in experience. Plots 3 and 4 show the experience profile of the learning parameter Θ_x and the productivity parameter of AFQT λ_x.

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 4 and present the results in Figure 3. 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 the choice of experience measure. The true productivity of AFQT in subplot 4, however, starts out lower and peaks at about 0.19 as opposed to 0.225 in Figure 2. Even after controlling for actual experience our main results

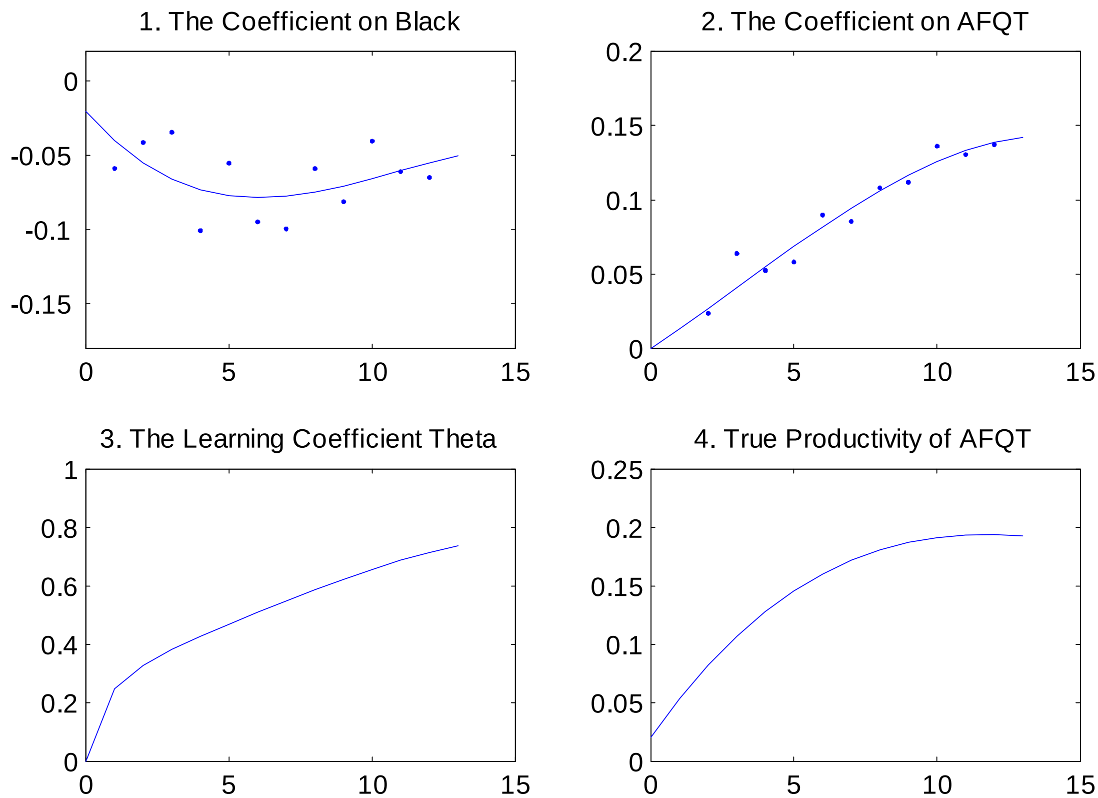

Figure 3: Here we fit our model controlling for actual experience. Plots 1 and 2 show the estimated coefficients $\beta_{x,Black}$ and $\beta_{x,AFQT}$. The estimates for $\beta_{x,AFQT}$ and $\beta_{x,Black}$ are smoothed using a cubic in experience. Plots 3 and 4 show the experience profile of the learning parameter Θ_x and the productivity parameter of AFQT λ_x.

from Table 2 remain: employers appear to statistically discriminate on the basis of race and learn about ability over time.

5 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 three 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. Finally, we show that the same patterns of ability revelation in the high school and college labor markets hold when using an alternative proxy for ability–father's education.

5.1 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 Butler and Heckman (1977) and 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 non-participants 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 regression 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 who 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 coefficient of .0174 (.0108), but increase sharply in ten years with a significant coefficient of .1407 (.0149). Blacks earn about twelve percent less than whites and this difference increases (although insignificantly) by an additional three percent in ten years. Specification (2) allows the coefficient on AFQT to vary by race. This specification again implies no differences in returns to AFQT, as the coefficients on the interactions of AFQT with race and experience are small in magnitude and statistically significant.

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 .1587 (.0341)

Table 5: The Effects of AFQT on Log Wages Controlling for Selection

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.1249**	-.1379**	.0611	.0343
	(.0219)	(.0540)	(.0538)	(.0662)
Standardized AFQT	.0174	.0268*	.1587**	.1413**
	(.0108)	(.0141)	(.0341)	(.0396)
Black x AFQT		-.0277		.0494
		(.0250)		(.0662)
AFQT x experience/10	.1407**	.1266**	-.0203	-.0255
	(.0149)	(.0196)	(.0624)	(.0719)
Black x experience/10	-.0313	-.0173	-.0845	-.0945
	(.0299)	(.0359)	(.0975)	(.1190)
Black x AFQT x exper/10		.0358		.0347
		(.0342)		(.1207)
Pseudo-R^2	0.0467	0.0467	0.0816	0.0825
No. Observations	13221	13221	3463	3463
Experience measure: Years since left school for the first time				

Note - In order to control for selection, 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. Potential experience is limited to less than ten and thirteen years for the high school and the college sample respectively. All specifications control for urban residence, a cubic in experience and year effects. The standard errors reported do not control for clustering at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

and these returns do not change over time: the coefficient on AFQT×exper/10 is small and insignificant with a magnitude of -.0203 (.0624). The results also suggest that college-educated blacks earn about the same as their white counterparts and that there are no significant racial differences in returns to AFQT in the college market.

5.2 College Versus the First Four Years of Experience in the HS 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 re-estimate the regressions in Tables 2 and 4 for high school graduates and 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 .0107 (.0200), and by ten years this return increases by .1201 (.0230). The same patterns can be seen in specification (2) where we also control for interaction of race dummies with AFQT and experience. The results of Table 6 confirm that ability is revealed much later in the high school labor market than in the college market.

5.3 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. In this subsection 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. Analogously to AFQT the returns to father's education increase significantly with experience implying that ten additional years of father's education yields a 16% increase in wages ten years after high school. These results do not change in specification (2) where we also include AFQT and its interaction with experience.

Table 6: College vs. Four Years of Experience After High School

	(1)	(2)	(3)	(4)
Model:				
Black	-.1023**	-.0911*	-.0722	-.0659
	(.0414)	(.0407)	(.0488)	(.0474)
Standardized AFQT	.0107	.0113	-.0067	-.0032
	(.0200)	(.0199)	(.0242)	(.0242)
AFQT x experience/10	.1201**	.1127**	.1359**	.1257**
	(.0230)	(.0226)	(.0281)	(.0275)
Black x experience/10	.0073	.0093	-.0200	-.0136
	(.0466)	(.0459)	(.0536)	(.0528)
Black x AFQT			.0588	.0493
			(.0431)	(.0421)
Black x AFQT x exper/10			-.0535	-.0445
			(.0489)	(.0480)
R^2	0.1372	0.1639	0.1375	0.1641
No. Observations	9239	9229	9239	9229

Note - 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 vs full time jobs. We exclude observations from the first four years in the labor market. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

Both AFQT and father's education have small and insignificant intercepts coupled with a positive and significant coefficients on the interactions with experience.

We now turn to specification (3), which analyses the effect of father's education on wages for college graduates. The coefficient on father's education is still statistically insignificant, but its magnitude of is quite sizable. The point estimate implies an 8.9% increase in earnings ten years out from a ten 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 about four times higher for college graduates than for high school graduates. The coefficient on father's education times experience enters is negative, small, and insignificant. This last coefficient was large and significant for high school graduates. The same results hold even after we include AFQT, although this decreases the immediate returns to father's education in the college market.

Table 7: The Effects of AFQT and Father's education on Log Wages

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.0530**	-.0536*	.0168	.1087*
	(.0269)	(.0305)	(.0567)	(.0596)
Father's Education/10	.0239	.0252	.0894	.0622
	(.0382)	(.0400)	(.0646)	(.0642)
Standardized AFQT		-.0004		.1328**
		(.0151)		(.0377)
Black x experience/10	-.1528**	-.0243	-.1060	-.0913
	(.0354)	(.0403)	(.0972)	(.1053)
F. Educ/10 x experience/10	.1632**	.0953*	-.0309	-.0397
	(.0539)	(.0532)	(.1123)	(.1105)
AFQT x experience/10		.1316**		.0461
		(.0203)		(.0628)
R^2	0.1327	0.1611	0.1340	0.1634
No. Observations	10077	10077	3289	3289
Experience measure: Years since left school for the first time				

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

* statistical significance at the 95% level

** statistical significance at the 99% level

Taken together, 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.

6 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 with labor market experience. In contrast, returns to AFQT for high school graduates are initially very close to zero and rise steeply with experience. Similar patterns emerge when father's education as an alternative correlate of ability. These results suggest that ability is observed perfectly for college graduates but is revealed to the labor market more gradually for high school graduates.

Consistent with the notion that ability is nearly perfectly revealed, we find no differences in wages or the returns to ability across race for our college sample. 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 six 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, Bishop (2006), Bishop (2005), and Bishop and Mane (2001). Exit exams would give employers a clearer signal of workers ability and would reduce their incentives to statistically discriminate.

7 Appendix

A Sample Creation

In this study we use the NLSY dataset for years 1979-2004. We only consider observations after the respondent has left school for the first time. Actual experience is counted as the total number of weeks that the respondent declares s/he has worked since last interview after they leave school for the first time. Potential experience is constructed as years since the respondent left school. Valid observations are kept even if the respondent goes back to school after leaving school for the first time but the additional years of education are subtracted from the experience measures.

Although the respondents report all the jobs held since the last interview, we only use the information of the current job they are holding at the time of the interview (CPS item). In addition, 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 CPS section of the NSLY. The real wage is created using deflators from the 2006 economic report of the president. All observations with wages less than $1 and more than $100 are dropped. Our education variable is the highest grade completed by the respondent at the time of interview. The AFQT variable is normalized by age since respondents took the AFQT at different ages.

There are 5404 non-hispanic males in the NLSY79 sample. We drop 373 respondents who never left school or do not declare when they first left school. Out of remaining respondents 1489 graduated before 1978. For this group we constructed the work history before 1978 using three set of questions from the 1979 interview as in AP. Out of them, 809 respondents were dropped since their work history could not be constructed.

Next we drop 13 individuals who by the 2002 interview did not have 8 years of education, 145 if the wage was missing, 203 if AFQT was missing, and 83 individuals who at the time of the interview were not working in civilian jobs for pay or whose wages were less than $1 or more than $100. The final sample contains 3778 individuals and 38168 observations.

After keeping only observations when the highest grade completed is 12 or 16 we are left with 2714 respondents and 23732 observations. If we were to construct the sample as AP by keeping observations before year 1993 and dropping the individuals who do not have a first occupation, the sample would contain 2968 individuals and 20753 observations (AP had 2976 individuals and 21058 observations).

B Replicating Altonji and Pierret (2001)

In this section we replicate the results reported on Altonji and Pierret (2001) using our sample selection criteria. AP estimate a log earning equation with linear interactions of education, race and AFQT with experience of the form:

$$\begin{aligned} w_i &= \beta_0 + \beta_1 s_i + \beta_2 r_i + \beta_3 z_i + \beta_{s,x}(s_i \times x_i) + \beta_{r,x}(r_i \times x_i) \\ &\quad + \beta_{z,x}(z_i \times x_i) + f(x_i) + \beta_\Phi' \Phi_i + \varepsilon_i \end{aligned} \tag{7}$$

Log wages w_i of individual i are given as a function of schooling s_i, race r_i, AFQT scores z_i, experience x_i, and other controls Φ_i.The results of the replication are presented in Table 8. Specification (1) uses the sample selection closest to AP with observations coming from interview years 1979-1992. The coefficients presented here differ slightly from those presented in AP because of few differences in sample construction. First, the construction of potential experience is slightly different. The potential experience measure here is years since first left school, and any years of additional education after entering the labor market are subtracted from the experience measure. This measure seems to capture the time a person actually spends in the labor market better than the experience measure in AP, which is simply age minus education minus seven. Secondly, we do not control for interactions of education and AFQT with time as that makes identification very hard and makes the estimates unstable. Regardless of the slight differences, the main qualitative results of AP are still present in the results presented in Table 8.

Following AP's interpretation, employers seem to statistically discriminate on the basis of education. The coefficient on education is positive and significant when a worker has no experience and falls as the worker gains more experience. On the other hand, employers initially put little weight on AFQT since it might not be visible to them. As the worker gets more experience the employers slowly learn about their ability so they increase the weight they put on AFQT. The coefficient on black is insignificant and small initially, but it becomes significant and negative over time. AP use these as evidence that there is statistical discrimination on the basis of education but not on the basis of race.

Column (2) uses the same specification for our whole sample for interview years 1979-2004. The results seem similar that the returns to AFQT are greater initially and have a flatter profile with experience. The change in the AFQT coefficients in the longer sample used in Column (2) is driven by a nonlinear relation between log wages and AFQT over experience. In order

Table 8: The Effects of AFQT and Schooling on Log Wages

	(1)	(2)	(3)
Model:			
Education	.0668**	.0725**	.0831**
	(.0058)	(.0045)	(.0051)
Black	-.0008	-.0244	-.0118
	(.0227)	(.0190)	(.0207)
Standardized AFQT	.0324**	.0602**	.0310**
	(.0116)	(.0010)	(.0107)
Education x experience/10	-.0240**	-.0042	-.0259**
	(.0076)	(.0038)	(.0068)
AFQT x experience/10	.0856**	.0496**	.0954**
	(.0159)	(.0079)	(.0137)
Black x experience/10	-.0735*	-.0639**	-.0737**
	(.0299)	(.0145)	(.0251)
R^2	0.2823	0.3357	0.3044
Sample	Replication of AP Years 1979-1992	Full sample Years 1979-2004	Full sample Experience<13
No. Observations	20617	37918	25726
Experience measure: Years since left school for the first time			

Note - Specification (1) is a replication of the results of AP. We also control year effects, a cubic in experience, a cubic in time with base year 1992, urban residence, and first occupation. Regression (2) uses the whole sample for years 79-04 and doesn't control for first occupation. We see a large coefficient on AFQT initially and a flat profile. Specification (3) limits the potential experience to less than 13 so the fast increase in the AFQT coefficient over time reappears. The White/Huber standard errors in parenthesiscontrol for possible correlation at individual level.

* significance level at the 95% level

** significance level at the 99% level

to keep the interpretation of the coefficients on AFQT simple we focus on the approximately linear part of this relationship, which corresponds to experience levels less than thirteen years. The regression using this criterion is presented in column (3) of Table 8. Restricting experience to less than thirteen years restores the low intercept and steep profile of AFQT. For the same reason explained above, we constrain the sample in our main analysis to experience levels less than 13 for high school graduates and less than ten for college graduates.

B.1 Sample Weights

Throughout this paper we have used both the nationally representative cross-sectional sample and the supplemental sample, which oversamples blacks and low-income whites, without using sample weights. Because our final sample is not representative of the U.S. population, questions may arise about whether we should be using weights in our estimation or not. There have been examples in the literature where weights have made a difference when using the NLSY79 data. For example, MaCurdy, Mroz and Gritz (1998) find differences in estimating the distributions of labor market earnings and hours of work when using weighted versus unweighted NLSY79 data. In order to address this concern, we estimate our key regressions using the sampling weights found on the NLSY79 and present the results in Table 9.

The results from for all specifications are very close in magnitude and not statistically different from the results previously presented in the unweighted regressions in Tables 2, Table 4 and Table 3. Because sampling weights do not make any difference in our results, we follow Altonji and Pierret (2001) as well as others in the literature in not including weights in presenting our main results.

C How College Reveals AFQT

Table 10 displays the coefficient estimates for regressions of AFQT on college major and standardized test scores. Rather than the individual coefficients we are interested in the general fit of the regressions. All of our specification control for major which is not shown. The R-squared in all of the specifications ranges from 0.567 when we only control for major and PSAT scores, to 0.733 when we control for major, SAT and PSAT scores.

D Model

In this appendix section we present a model of statistical discrimination that we estimate in section 4. 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.[25]

[25] Whether or not employers have private information about workers is an open question in the literature. Our assumption is supported by findings in Schoenberg (2007) who reports that for white high school graduates learning

Table 9: Main Regressions Using Sample Weights

	High School		College	
	(1)	(2)	(3)	(4)
Model:				
Black	-.0922**	-.0694*	.0140	.0117
	(.0313)	(.0325)	(.0613)	(.0725)
Standardized AFQT	-.0045	-.0089	.1159**	.1149*
	(.0157)	(.0177)	(.0425)	(.0475)
AFQT x experience/10	.1224**	.1250**	.0526	.0614
	(.0203)	(.0231)	(.0723)	(.0813)
Black x experience/10	-.0256	-.0401	.0103	.0310
	(.0389)	(.0406)	(.1054)	(.1208)
Black x AFQT		.0336		.0058
		(.0292)		(.0794)
Black x AFQT x exper/10		-.0215		-.0620
		(.0395)		(.0133)
R^2	0.1562	0.1564	0.1532	0.1533
No. Observations	11798	11798	3318	3318

Note - In all specifications we control for urban residence, a cubic in experience and year effects. Potential experience is limited to less than ten and thirteen years for the high school and the college sample respectively. The college sample excludes blacks at the top tenth percentile of the AFQT distribution. The White/Huber standard errors in parenthesis control for correlation at the individual level.

* statistical significance at the 95% level

** statistical significance at the 99% level

We specify the true log-productivity of a worker as:

$$\chi_{i,x} = f(s_i) + \lambda_x(z_i + \eta_i + q_i) + \tilde{H}(x) \tag{8}$$

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 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.[26] Finally,

appears to be symmetric, meaning firms do not have any private information. Since we find there is no racial differences in the returns to AFQT, learning should be symmetric for high school graduate blacks too.

[26]The lack of separate coefficients for z, η, q is without loss of generality since we can define η and q such that

Table 10: Predicting the AFQT for College Graduates

	(1)	(2)	(3)	(4)
Model:				
Dep. Variable: AFQT				
SAT Math Sect./10	.0234**		.0080	
	(.0037)		(.0051)	
SAT Verbal Sect/10	.0150**		.0112*	
	(.0036)		(.0052)	
PSAT Math Sect./10		.2712**	.1934**	
		(.0271)		
PSAT Verbal Sect./10		.0591*	-.0030	
		(.0288)	(.0537)	
ACT Math Sect./10				.3248**
				(.0488)
ACT Verbal Sect./10				.0345**
				(.0711)
Constant	-.7238**	-.4373**		-.2477*
	(.1432)	(.1119648)		(.1105)
R^2	0.5984	0.5674	0.7325	0.5995
No. Individuals	178	254	119	188

Note. - All the specifications above control for college major.
* significance level at the 95% level
** significance level at the 99% level

$\tilde{H}(x)$ 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.[27] 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

their coefficients are the same as that of z.

[27] In all the specifications of Table 2 and Table 4, 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.

$\eta \mid (s, q)$ is linear in (s, q):

$$\eta = \alpha_1 s + \alpha_1 q + v \tag{9}$$

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

$$z = \bar{z} + e \tag{10}$$

Substituting equation (10) in (8) we can write the initial log-productivity at $x = 0$ as:

$$\begin{aligned} \chi &= rs + \lambda_0(\bar{z} + e + \eta + q) + \tilde{H}(0) \\ &= E(\chi|\bar{z}, q) + \lambda_0(e + \eta) \end{aligned} \tag{11}$$

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:

$$y_x = z + \eta + \varepsilon_x \tag{12}$$

where ε_x is independently distributed over time as a normal with a time dependent variance σ_x^2. We maintain that ε_x is orthogonal to all other variables in the model.

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:

$$\mu_0 = \bar{z} + \alpha_1 s + \alpha_1 q \tag{13}$$

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:

$$\mu_x = (1 - \theta_x)\mu_{x-1} + \theta_x y_x \tag{14}$$

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:

$$E_x(\chi|\bar{z}, q, s, Y^x) = rs + \lambda_x q + \lambda_x \left[(1 - \theta_x)\mu_{x-1} + \theta_x y_x\right] + \tilde{H}(x) \tag{15}$$

where $Y^x = \{y_{1,}...y_x\}$.As employers learn more and more the term $\left[(1-\theta_x)\mu_{x-1}+\theta_x y_x\right]$ 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:

$$W = E[\exp(\chi)|\bar{z}, q, s, Y^x] \tag{16}$$

The normality assumptions above imply that the distribution of χ conditional on (s, q, Y^x) is normal. We can then write log wages as:[28]

$$w_x = \lambda_x \left[(1-\theta_x)\mu_{x-1}+\theta_x y_x\right] + C_x \tag{17}$$

where

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

Equation (17) gives the wages paid to a worker given $(\bar{z}, q, s, Y^x)$. We cannot observe q and Y^x, so in order 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 fist step to doing this is to define a linear projection of (q, η) :

$$\begin{aligned} q &= \gamma_1 s + u_1 \\ \eta &= \gamma_2 s + u_1 \end{aligned} \tag{18}$$

This allows us to determine log wages as a function of only $(\bar{z}, z, s, x)$. This linear projection is given by:[29]

$$E^*(w_x|z,s) = \lambda_x \left[(1-\theta_x)E^*(\mu_{x-1}|z,s) + \theta_x E^*(y_x|z,s)\right] + c_x \tag{19}$$

where

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

Substituting in eq. (19) for μ_x as given in eq. (14), and for q given in eq. (18), we can write log wages at $x = 1$ as:

$$w_1 = \lambda_1 \left[(1-\theta_1)\bar{z} + \theta_1 z\right] + k_1 \tag{20}$$

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

[29] Here $E^*(X|Y)$ denotes the linear projection of X on Y.

where:

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

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:

$$w_x = \lambda_x \left\{ \prod_{i=i}^{x}(1-\theta_i)\bar{z} + \left[1 - \prod_{i=i}^{x}(1-\theta_i)\right] z \right\} + k_x \tag{21}$$

where

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

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

$$w_x = \lambda_x \left\{(1-\Theta_x)\bar{z} + \Theta_x z\right\} + k_x \tag{22}$$

which is our estimating equation in section 4. Note that as experience increases the weight on $\bar{z}$ goes to zero and the weight on z to one since, as long as employers are getting new signals every period, $\prod_{i=i}^{x}(1-\theta_i) \to 0$.

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