The Changing Roles of Education and Ability in Wage Determination

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This study examines changes in returns to formal education and cognitive skills over the past 20 years using the 1979 and 1997 waves of the National Longitudinal Survey of Youth. We show that cognitive skills had a 30%–50% larger effect on wages in the 1980s than in the 2000s. Returns to education were higher in the 2000s. These developments are not explained by changing distributions of workers' observable characteristics or by changing labor market structure. We show that the decline in returns to ability can be attributed to differences in the growth rate of technology between the 1980s and 2000s.

I. Introduction

Families and policy makers implement various strategies to enhance an individual's capacity to succeed in the labor market. Investment in an individual's human capital is one of the most important channels to achieve this goal. A large literature documents that workers with higher educational attainment have higher earnings and that this wage differential has been increasing over time. The standard estimates show that between the 1980s and

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2000s, there was an increase in returns to education in the range of 20%–50% (see, e.g., Goldin and Katz 2007). Many studies argue that this growth was more rapid in the first half of the 1980s. There is also a debate about the interpretation of the rising return to schooling: whether it is due to an increase in the return to formal education or a rising return to cognitive ability. This debate focuses on developments in the 1980s and concludes that the increase in return to cognitive ability explains much of the increase in return to education in the 1980s (see, e.g., Cawley et al. 1998). In this study, we examine changes in wage structure between the 1980s and 2000s and show that the return to cognitive skills has declined substantially over this period while the return to schooling has increased.

Using data from the 1979 and 1997 National Longitudinal Surveys of Youth (NLSY79 and NLSY97, respectively), we evaluate to what extent schooling and cognitive skills, as captured by performance on the Armed Services Vocational Aptitude Battery (ASVAB) tests,[1] affect the wages of 18–28-year-old men and women and how this relationship has changed between the 1980s and 2000s.[2] We show that during these 2 decades the return to cognitive ability declined by 30%–50% for men and women. We also show that the slowdown in the growth rate of return to education after the 1990s is less pronounced when controlling for ability. These changes in returns are persistent across various demographic groups and are robust to use of alternative ability measures and econometric specifications.

We consider various channels that could lead to such large declines in the ability premium in the 2000s. First, we examine changes in the distributions of demographic characteristics and assess how the returns to education and ability would have changed if observable characteristics remained constant between the 1980s and 2000s. We reweight the samples to match NLSY79 and NLSY97 age and family background distributions, and we find that changing demographics cannot explain the decrease in return to cognitive ability. Second, we match distributions of occupations and industries across surveys, and we show that changes in the labor market structure do not explain the results. Third, we examine the role of measurement error in test scores and show that it cannot explain our findings.

To further study skill prices in the 1980s and 2000s, we examine changes in wage dynamics. In the 1980s estimations, returns to education decline with experience and returns to ability increase with experience. These relationships are weaker in the 2000s for men and women. In the dynamic model, the returns to cognitive skills for entry wages are similar across cohorts, which suggests that changing wage dynamics explain the overall decline in

[1] The ASVAB scores are extensively used in the literature as a measure of cognitive achievement, aptitude, and intelligence. See, e.g., Carneiro and Heckman (2002) and Belley and Lochner (2007).

[2] The data are from the 1980–91 waves in NLSY79 and the 1999–2008 waves in NLSY97.

returns to cognitive skills. We address these outcomes within two frameworks, human capital accumulation theory, as in Ben-Porath (1967), and the employer-learning model (see, e.g., Farber and Gibbons 1996; Altonji and Pierret 2001). Within the Ben-Porath framework, changing coefficients of the dynamic wage equation reflect how changing technology and structural changes in the labor market affect human capital accumulation. Using this framework, we examine the Nelson-Phelps hypothesis, which posits that skills are most valuable when workers are adapting to a changing environment but that as the rate of technological change slows down, formal education becomes relatively more important for labor market outcomes. Within the employer-learning framework, changing wage dynamics reflect changes in signaling, screening, and learning mechanisms that are associated with reforms in the education system following technological innovations. Both explanations are consistent with a changing state of workplace technology. We construct technology growth indexes employing the Cummins and Violante (2002) methodology and show that there was a slowdown in growth starting in the late 1990s (Greenwood and Yorokoglu [1997] and Katz [2000] show similar trends). We also argue that changing technology has led to reforms in the schooling system, which has resulted in a more relevant and merit-oriented education.

Previous studies that examine changes in returns to cognitive skills focus on developments in the 1980s and find an increasing or weakly increasing trend. For example, Blackburn and Neumark (1993) use 1979–87 waves of the NLSY79 and report that the rise in return to education during that period was concentrated among those with both high education and high ability.[3] Grogger and Eide (1995), using 1970s to 1980s data, find that controlling for ability reduces the rising return to schooling.[4] Bishop (1991), using the 1981–86 waves of NLSY79, finds that the return to cognitive skills rose in cross-sectional data but finds mixed results using panel data. All the above studies decompose the increasing return to schooling using panel data or repeated cross-sections data and therefore cannot simultaneously identify age, cohort, and time effects. These studies require further parametric assumptions to conclude whether the estimated increase in return to ability is due to changes in the value of cognitive skills or because ability becomes more valuable with work experience. Heckman and Vytlacil (2001) provide an extensive study using a large number of specifications and demonstrate the sensitivity of the results to such assumptions.

[3] Blackburn and Neumark (1993) measure cognitive ability using an average score of three subtests in the ASVAB.

[4] Grogger and Eide (1995) use the National Longitudinal Study of the High School Class of 1972 (NLS72) survey and the High School and Beyond (HSB) survey. Cognitive skills are measured by standardized test scores and high school grades. They use a math test, a vocabulary test, and a "mosaic" test that measures perceptual speed and accuracy.

Murnane, Willett, and Levy (1995) solve the identification problem by examining two different cohorts. They draw from the NLS72 and High School and Beyond surveys to compare wages of 24-year-old males in 1978 and 1986. They conclude that 38% of the rise in the return to education during this period can be attributed to a rise in the return to ability (measured by scores on a math test). There is still a question of whether their results are unique to the age they choose and the 2 years they analyze.

An alternative to estimating the trend in the return to cognitive ability (as measured by scores on standardized tests) is to examine patterns of wage dispersion. For example, Juhn, Murphy, and Pierce (1993) attribute the increasing variance of wage residuals in the 1980s to an increase in the demand for unobserved skill. Chay and Lee (2000) examine the changing distributional patterns and show that the return to unobserved skills were increasing in the 1980s, but they argue that it cannot be large enough to account for the full increase in the return to schooling. Taber (2001) finds that an increase in the demand for unobserved ability could play a major role in the growing college premium.

Our study extends the previous work by using cross-decade comparisons of the returns to schooling and cognitive ability. Using two NLSY cohorts allows us to identify age, cohort, and time effects. Whereas previous studies have focused on developments in the 1980s and early 1990s, we examine the 1980s–2000s period and document a large decline in the return to cognitive skills and an increase in the return to schooling.

This article proceeds as follows. Section II describes the data sets in detail. Our main empirical results are reported in Section III. In this section, we examine the changing roles of cognitive skills and formal education in wage determination. We also perform sensitivity analysis to evaluate whether differences in demographics and test-taking conditions can explain the outcomes. Section IV explores the dynamics of wages and evaluates findings within the human capital and employer-learning theories. Here we also document the developments in the state of technology over the 20 years. Section V concludes the article.

II. Data

The data are from the 1979 and 1997 waves of the National Longitudinal Survey of Youth (NLSY). NLSY79 provides a nationally representative sample of 12,686 young men and women who were 14–22 years old in 1979, and NLSY97 samples 8,984 individuals who were 12–16 years old in 1997. We employ both cross-sectional and supplemental samples (excluding the military supplement) and use the base year weights provided by the Bureau of Labor Statistics (BLS) to achieve representativeness of the population.[5]

[5] For some estimations we construct alternative sets of weights to evaluate effects of changing distributions of demographic characteristics on labor market outcomes.

We pool observations for 1980–91 for NLSY79 and for 1999–2008 for NLSY97.

The data contain detailed information on individuals, including measures of cognitive ability, education, labor market activity, and other family and personal characteristics. Many of these variables are compatible across the 1979 and 1997 cohorts, but some require further adjustments to facilitate comparison across samples. Altonji, Bharadwaj, and Lange (2012) provide a detailed analysis of each data set and suggest methods to achieve compatibility. We follow their methodology where applicable.[6]

Individuals enrolled in school and in military service are excluded from the analysis. We consider individuals who have achieved their highest degree, work at least 20 hours per week, and earn real hourly wages within the range of \$3–\$100 (in 2007 prices, deflated using the CPI). We exclude individuals with missing information on key variables. Since the oldest individual in the NLSY97 turned 28 in the 2008 wave of data, we limit our analysis to the 18–28 age group.[7] The final samples of men contain 25,491 observations in the 1979 cohort and 12,458 in the 1997 cohort. The number of individuals in each cohort is 5,021 and 3,009, respectively. Women samples contain 21,603 observations in the NLSY79 and 10,887 observations in NLSY97, pooling information on 4,863 and 2,892 respondents, respectively.

Table 1 summarizes the key variables. The statistics are calculated using the standard BLS weights and also using constructed weights to match the age distribution of NLSY97 to that of NLSY79.[8] Comparison of the age statistics in the NLSY79 and NLSY97 samples shows the main effect of the age-reweighting procedure. The mean age is lower in NLSY97 when using the standard weights due to a higher concentration of young workers. The age statistics are practically identical when adjusting the NLSY97 sample to have the age distribution of NLSY79. Other variables that are sensitive to the choice of weights are hourly wage, work experience, and education. The means of these variables increase when the age-reweighted NLSY97 sample is used.

Both data sources contain comparable measures of ability, captured by the ASVAB, which is a sequence of tests that cover basic math, verbal, and manual skills. Math skills are measured by scores on the Arithmetic Reasoning, Numerical Operations, and Mathematics Knowledge sections of the ASVAB. Verbal skills are measured by the scores on the Word Knowledge

[6] Some studies have raised a concern regarding the representativeness of the NLSY97. These issues are discussed in detail by Altonji et al. (2012), and we adopt their assumption that when using the survey weights, the available data are representative of the 1997 and 1979 populations. Altonji et al. (2012) also argue that attrition patterns do not constrain the analysis.

[7] A very small number of respondents were age 29 at the time of the 2008 wave of the NLSY97.

[8] The reweighting procedure is discussed in detail in Subsec. III.A.

Table 1
Summary Statistics

	Men						Women					
	NLSY79		NLSY97				NLSY79		NLSY97			
	Standard Weights		Standard Weights		Age-Reweighted		Standard Weights		Standard Weights		Age-Reweighted	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Real wage rate	14.73	7.30	13.77	8.07	15.22	9.31	11.87	5.63	11.88	6.24	12.94	7.42
AFQT	160.18	31.21	161.68	32.21	158.64	33.31	165.64	27.27	164.85	28.90	160.62	31.02
Math score	47.83	8.15	48.46	8.84	48.03	8.98	46.51	6.68	49.33	8.08	48.60	8.40
Verbal score	44.88	9.89	45.24	10.22	44.11	10.66	47.43	8.72	46.57	9.33	45.09	10.06
High school	.66	.47	.70	.46	.66	.47	.69	.46	.63	.48	.60	.49
Associate's	.04	.18	.04	.20	.04	.20	.06	.24	.05	.23	.06	.24
Bachelor's	.12	.32	.13	.33	.16	.36	.14	.35	.20	.40	.21	.41
Master's	.01	.10	.01	.09	.02	.12	.01	.10	.02	.13	.03	.18
Years of school	12.28	2.00	12.57	2.16	12.71	2.42	12.68	1.89	13.10	2.33	13.33	2.55
Age	24.78	2.36	22.68	2.32	24.77	2.37	24.73	2.36	22.81	2.30	24.72	2.37
Experience	6.50	2.61	4.11	2.75	6.05	3.18	6.04	2.57	3.71	2.68	5.39	3.16
Black	.13	.33	.15	.36	.25	.43	.13	.34	.17	.37	.30	.46
Unemployment	.08	.01	.05	.00	.05	.00	.08	.01	.05	.00	.05	.00
N	25,491		12,458				21,603		10,887			
Family background:												
Family intact	.80	.40	.68	.47	.60	.49	.80	.40	.63	.48	.61	.49
Mother's education	11.57	2.40	12.77	2.57	12.68	2.74	11.56	2.39	12.82	2.57	12.59	2.82
Father's education	11.62	3.21	12.59	2.84	12.41	2.97	11.69	3.22	12.72	2.87	12.51	3.01
N	20,449		10,359				17,802		8,958			
Family income												
Ln(real family income)	10.72	.73	10.81	1.09	10.76	1.12	10.79	.67	10.61	1.18	10.52	1.20
N	11,791		10,062				9,437		8,948			

NOTE.—Hourly wages are inflation adjusted to 2007 using the CPI-U. AFQT score is adjusted using the Altonji et al. (2008) methodology. Education variables: high school = 1 for high school graduates and 0 otherwise, associate's = 1 for individuals with an associate degree, bachelor's = 1 for bachelor's degree holders, and master's = 1 for individuals with a master's degree or higher. The unemployment rate is measured by a 3-year moving average and is calculated using the Current Population Survey. Family background variables are observed only for a subset of individuals. Real family income is measured at ages 16 or 17. Family intact indicates family composition at 14 years old in the NLSY79 and in 1997 (i.e., ages 13–17) in the NLSY97. Parental education is measured in years of schooling.

and Paragraph Comprehension sections of the ASVAB. We construct the Armed Forces Qualifications Test (AFQT) score using the definition from NLSY79, which is based on scores from Arithmetic Reasoning, Numerical Operations, Word Knowledge, and Paragraph Comprehension tests. We also define Math and Verbal measures using the relevant tests in ASVAB. "Math" is defined as an average of the Arithmetic Reasoning, Mathematics Knowledge, and Numerical Operations sections. "Verbal" ability is measured by averaging the scores on the Word Knowledge and Paragraph Comprehension sections of the ASVAB.

We address two important compatibility issues that arise due to differences in survey and test methodologies between the NLSY79 and NLSY97. First, participants in the NLSY79 took the ASVAB exam in the summer of 1980 when they between 15 and 23 years old. For the NLSY97 cohort, the test was administered when individuals were between 12 and 17 years old. Second, the NLSY79 cohort was administered a pencil-and-paper (P&P) version of the ASVAB, while the NLSY97 participants took a computer-assisted test (CAT) format. For NLSY97, we use ASVAB scores provided by Daniel Segall, who develops a mapping that assigns scores to equalize percentiles on the various subtests of the P&P and the CAT. The mapping procedure is described in detail in Segall (1997). To adjust the scores by age, we follow a procedure described in Altonji et al. (2012).[9] For the NLSY79 and NLSY97, we apply an equipercentile mapping to age 16 of the scores of respondents who took the test at other ages, exploiting the overlap in the test-taking age across cohorts.

Figure 1 shows the distributions of ability measures for each cohort. Table 1 provides means and standard deviations of the measures. The AFQT score can take values between 70 and 280, but actual scores fall within the 80–220 range. Math and verbal test scores can range within 20 and 80, with actual scores falling within the 20–70 interval. We use normalized test scores in estimations, such that the relevant sample mean is zero and the standard deviation is one.

The ASVAB scores are widely used in the literature as a measure of cognitive achievement, aptitude, and intelligence. Some studies argue that human capital investments affect AFQT scores, which may constrain the identification of education and ability effects on earnings (see, e.g., Neal and Johnson [1996] or Cascio and Lewis [2006]). To address this issue, we perform robustness tests using a subgroup of individuals who took the AFQT when they were 16 years old (the overlap age in the two samples) and attended the ninth grade. Another concern is that individuals with higher AFQT scores are more likely to be more educated and that such selection into schooling could change over time. We find that the correlation between the AFQT scores and years of schooling is fairly stable, 0.56 in NLSY79 and

[9] We thank Joseph Altonji, Prashant Bharadwaj, and Fabian Lange for help with the ASVAB data.

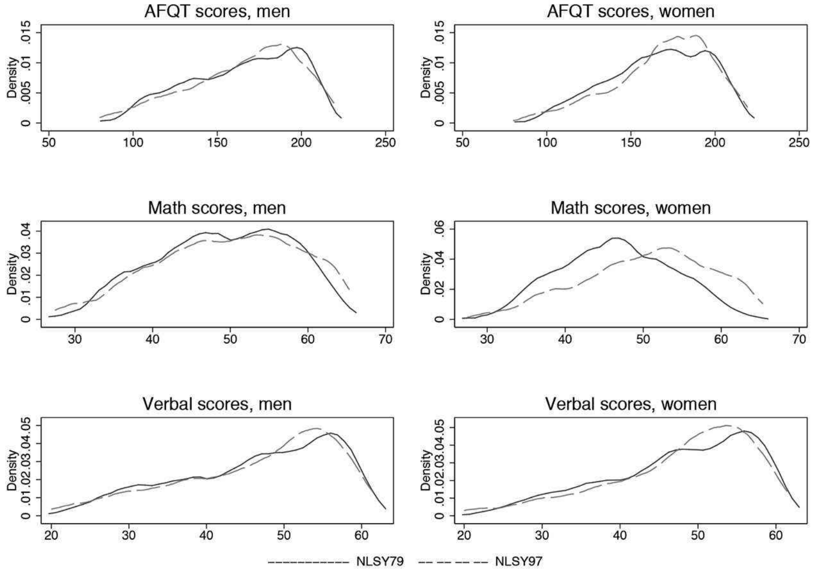

FIG. 1.—Ability measures. Both populations are weighted using the BLS weights

0.53 in NLSY97 for males and 0.52 versus 0.56 for females (using the age reweighted sample), which allows us to compare returns to cognitive skills and education across cohorts.

Table 1 documents an increase in the schooling level, which is more pronounced when using the age-reweighted NLSY97 sample. The average of years of schooling in the NLSY79 sample is 12.3 for men and 12.7 for women. In the NLSY97 sample, the averages are 12.6 for men and 13.1 for women. In the age-reweighted NLSY97 sample, the averages are 12.7 and 13.3 for men and women, respectively. On the other hand, it takes longer for the 1997 cohort to complete their degrees. For example, an average 25-year-old college graduate has 15.9 years of schooling in NLSY79 but 16.5 years in NLSY97. Therefore, in our main estimations, we use indicators of schooling levels that show similar patterns as the continuous schooling variable.

Work experience is defined as age minus schooling minus 6; the average experience is slightly lower for the NLSY97 cohort (age-reweighted sample). Hourly wage rates (in 2007 dollars) increase over time if using the age-reweighted samples. To control for changing macroeconomic conditions, we use the unemployment rate. Finally, the proportion of black workers is higher in the NLSY97 sample. This is partially due to sampling methodology and partially due to higher attrition of black workers in the earlier waves of the survey. This issue is discussed in more detail in Altonji et al. (2012).

Table 1 also summarizes information on the family background of respondents: parental education, family structure, and family income. The

NLSY79 and NLSY97 record family income in early survey years; we use average family income (in 2007 dollars) when participants were 16–17 years old, excluding those not living with their parents at that time.[10] Mean family income is fairly constant over time, but its dispersion has risen. Family structure information is provided by an indicator variable for whether both parents were living with the child when he or she was 14 years old in the NLSY79 and in 1997 (i.e., ages 13–17) in the NLSY97. There are more single-parent households in the later cohort. Finally, table 1 shows statistics on parental years of schooling, which are higher in the 2000s.

III. Estimation

We estimate wage functions for men and women using the NLSY79 and NLSY97. The tables summarize selected results; full tables are provided in the appendix, available in the online version of *Journal of Labor Economics*.[11] To evaluate the changes in effects of schooling and cognitive skills on earnings, we estimate

$$\begin{aligned}\ln \text{wage}_{it} = {} & \beta_1^T \text{ EDUC}_i + \beta_2^T \text{ ABILITY}_i + \beta_3^T \text{ EXP}_{it} \\ & + \beta_4^T \text{ EXP}_{it}^2 + \beta_5^T X_{it} + \varepsilon_{it},\end{aligned} \tag{1}$$

where wage_{it} is the real hourly wage rate paid to an individual i at time t, EDUC_i is a vector of education dummy variables, ABILITY_i measures cognitive skills using the AFQT score, the average Math score or the average Verbal score, EXP_{it} corresponds to labor market experience, X_{it} is a vector of personal characteristics and family background variables. Superscripts on the coefficients denote the cohort, $T \in \{\text{NLSY79}, \text{ NLSY97}\}$. The term ε_{it} is a vector of unobserved factors that affect wages (e.g., ambition or luck). We assume that correlations between ε_{it} and control variables do not change over time (allowing for zero correlation). This assumption allows us to compare the coefficients of equation (1) across cohorts. The plausibility of this assumption is to some extent explored in our estimations that include ability measures and detailed vectors of controls.

The data sets pool information for individuals over time. Therefore, the coefficients of education and ability may reflect not only prices of these skills but also the effects of human capital depreciation and on-the-job training or learning-by-doing. We discuss the interpretation of the coefficients in the next subsection, where we estimate the returns to formal schooling and test scores in a dynamic wage model.

The results are reported in table 2. Columns 1 and 2 show the estimated effects of education on wages without controlling for test scores. Returns

[10] The family income measure is available for the younger cohorts of NLSY79, those born between 1961 and 1964. When income is available only for age 16 or age 17 and not both, we use the available measure.

[11] For more details, see the notes of each table.

Table 2
Returns to Schooling and Cognitive Skills, Standard Weights, Ordinary Least Squares

	AFQT80				Math		Verbal	
	NLSY79 (1)	NLSY97 (2)	NLSY79 (3)	NLSY97 (4)	NLSY79 (5)	NLSY97 (6)	NLSY79 (7)	NLSY97 (8)
Men:								
Test score			.0956	.0328	.1109	.0460	.0672	.0190
			(.0088)	(.0079)	(.0084)	(.0080)	(.0084)	(.0079)
High school	.2012	.1901	.1239	.1679	.1144	.1620	.1495	.1772
	(.0161)	(.0193)	(.0176)	(.0197)	(.0172)	(.0199)	(.0175)	(.0197)
Associate's	.3836	.4415	.2727	.4143	.2645	.4068	.3065	.4255
	(.0335)	(.0445)	(.0357)	(.0446)	(.0352)	(.0448)	(.0353)	(.0446)
Bachelor's	.5248	.5972	.3845	.5481	.3743	.5272	.4323	.5706
	(.0233)	(.0279)	(.0264)	(.0300)	(.0252)	(.0303)	(.0262)	(.0297)
Master's	.8308	.9112	.6520	.8552	.6282	.8333	.7188	.8807
	(.0510)	(.0824)	(.0531)	(.0819)	(.0527)	(.0816)	(.0528)	(.0824)
R^2 (adjusted)	.1405	.1498	.1661	.1535	.1758	.1570	.1544	.1511
N	25,491	12,458	25,491	12,458	25,491	12,458	25,491	12,458
Women:								
Test score			.1078	.0624	.1059	.0654	.0824	.0506
			(.0077)	(.0079)	(.0076)	(.0081)	(.0074)	(.0073)
High school	.2167	.1979	.1334	.1563	.1473	.1587	.1518	.1643
	(.0157)	(.0175)	(.0164)	(.0179)	(.0160)	(.0180)	(.0166)	(.0177)
Associate's	.4773	.4723	.3500	.4042	.3649	.4032	.3854	.4197
	(.0293)	(.0380)	(.0297)	(.0391)	(.0292)	(.0384)	(.0301)	(.0392)
Bachelor's	.6194	.6695	.4581	.5815	.4741	.5766	.5039	.6029
	(.0237)	(.0246)	(.0263)	(.0266)	(.0253)	(.0266)	(.0263)	(.0262)
Master's	.7919	1.0034	.6168	.9038	.6328	.9025	.6697	.9274
	(.0764)	(.0556)	(.0750)	(.0560)	(.0734)	(.0551)	(.0757)	(.0565)
R^2 (adjusted)	.1910	.2579	.2257	.2713	.2270	.2729	.2130	.2673
N	21,603	10,887	21,603	10,887	21,603	10,887	21,603	10,887

Note.—All statistics are weighted by the cross-sectional weights. Wages are inflation adjusted to 2007 using the CPI-U. Test scores are normalized to have zero mean and standard deviation one. Education variables: high school = 1 for high school graduates and 0 otherwise, associate's = 1 for individuals with an associate degree, bachelor's = 1 for bachelor's degree holders, and master's = 1 for individuals with a master's degree or higher. Other included controls: experience, experience^2, black, unemployment, metro status. For full results, see tables A1 and A2 in the online appendix. Respondents are clustered at the primary sampling unit, and robust standard errors are reported in parentheses.

to education in this specification display modest increases over time for men and women. Columns 3–8 display estimation results that include the ability measures. We document a significant decline in return to ability, β_2, over the 20 years. The differences between the coefficients on ability measures are statistically significant at the 1% confidence level in all specifications. For men, an increase in the AFQT score by one standard deviation is associated with a 9.6% increase in hourly wage for the 1979 cohort, but only with a 3.3% increase for the 1997 cohort. For women, the effect of one standard deviation increase in AFQT score on the real wage rate drops from 10.8% to 6.2%. Similar large declines in the returns to cognitive skills are documented when using alternative measures; the coefficient of Math (Verbal) score has declined by 59% (72%) for men and by 38% (39%) for women.

The increase in the return to education is more pronounced when controlling for test scores. For instance, if not controlling for ability, the return to a bachelor's degree (compared to high school dropouts) for men is 14% higher in the 2000s than in the 1980s, and this difference increases to 43% if controlling for AFQT (for women these changes are 8% and 27%, respectively). These outcomes also imply that the ability bias is larger when estimating the wage equation for the 1980s.[12]

Table 3 reports estimation results of the wage equation controlling for additional characteristics, as well as by education level and by race. Including family background controls (model 1, panel A) such as family income, parental education, and intact family indicator reduces the coefficient of the AFQT score. Adding occupation and industry indicators (model 2, panel A) reduces the coefficients of AFQT further. However, the proportional decline in the AFQT coefficient does not change much when including additional controls, and the differences in the returns to cognitive skills between the 1980s and 2000s are statistically significant for men and women.

Returns to ability by education level are reported in panel B of table 3. These results show that the decrease in the returns to ability occurred within and between different education levels for men and women. The differences in the ability coefficients across cohorts are statistically significant at the 1%–5% level in all specifications. The same pattern is observed in panel C, table 3, which records estimation results by race. The returns to ability decrease for white and black men and women, although the magnitude of the decline is higher for white workers. The differences are significant at the 1% level for men and at the 5%–10% level for women.

Equation (1) is also estimated using the alternative definition of the schooling variable. Columns 1, 2 and 5, 6 in table 7 report estimation results using years of schooling (highest grade completed) for men and

[12] Returns to experience for both cohorts do not change significantly when controlling for the AFQT scores. See table A1 in the online appendix.

Table 3
Returns to AFQT, Standard Weights, Ordinary Least Squares, with Additional Controls, by Education and by Race

	Men			Women		
	AFQT	R^2 (Adjusted)	N	AFQT	R^2 (Adjusted)	N
Panel A:						
Model 1:						
NLSY79	.0683	.2396	9,396	.0952	.2783	7,788
	(.0121)			(.0132)		
NLSY97	.0248	.1593	8,432	.0682	.2856	7,480
	(.0101)			(.0108)		
Model 2:						
NLSY79	.0608	.3113	9,387	.0742	.3659	7,775
	(.0110)			(.0121)		
NLSY97	.0224	.3054	8,408	.0479	.4139	7,467
	(.0089)			(.0093)		
Panel B: by education:						
High school dropouts:						
NLSY79	.1134	.0940	5,875	.0665	.0410	2,826
	(.0196)			(.0190)		
NLSY97	.0199	.0474	1,846	.0528	.0237	1,284
	(.0173)			(.0194)		
High school diploma:						
NLSY79	.0836	.0816	16,297	.1017	.0755	14,993
	(.0108)			(.0088)		
NLSY97	.0316	.0658	8,496	.0661	.0463	6,835
	(.0094)			(.0092)		
Bachelor's:						
NLSY79	.1594	.1044	2,346	.1639	.1360	2,476
	(.0249)			(.0275)		
NLSY97	.0404	.0404	1,066	.0648	.0203	1,377
	(.0386)			(.0282)		
Panel C: by race:						
White:						
NLSY79	.0901	.1464	15,956	.1038	.2236	13,815
	(.0106)			(.0092)		
NLSY97	.0276	.1380	6,762	.0567	.2753	5,507
	(.0105)			(.0109)		
Black:						
NLSY79	.1213	.1356	6,439	.1401	.1777	5,250
	(.0143)			(.0144)		
NLSY97	.0700	.1356	3,137	.0985	.2896	3,146
	(.0136)			(.0120)		

NOTE.—All statistics are weighted by the cross-sectional weights. Wages are inflation adjusted to 2007 using the CPI-U. Test scores are normalized to have zero mean and standard deviation one. Other controls: education dummies (see table 2 note), experience, experience^2, black, unemployment, metro status. Coefficients and standard errors presented. Model 1 specifications include family background variables. Model 2 specifications include family background variables and industry and occupation dummies. For full results, see tables A3, A4, A5, and A6 in the online appendix. Respondents are clustered at the primary sampling unit, and robust standard errors are reported in parentheses.

women. In these specifications, the AFQT coefficient drops from 0.077 to 0.030 for men and from 0.091 to 0.070 for women.

A. Measurement Errors

We provide robustness and sensitivity analysis of our results. First, we check whether measurement error in test scores can explain the outcomes. Second, we estimate equation (1) using weights to adjust the age and other characteristics distributions that vary across samples. Third, we estimate returns to skills while reweighting the NLSY97 sample to match labor market structure in the 1980s.

Section II describes the procedure to adjust the scores for the test format and for differences in the test-taking age. To eliminate measurement errors associated with the age adjustments, we estimate equation (1) for respondents who took the ASVAB test when they were 16 years old. Results in table 4 show a significant decline in returns to ability over the 20 years for men and women. The differences are statistically significant at the 5% level for men and at the 1% level for women.[13]

To further examine the role of potential measurement errors, we perform TSLS estimations using the SAT score to instrument for the AFQT score.[14] The two-stage least squares (2SLS) results, along with the ordinary least squares (OLS) results for the subsample of respondents with valid SAT scores, are reported in table 5. The first stage result s show a strong correlation between the SAT and AFQT scores, which did not change much over time. The second stage results show larger effects of AFQT on earnings than the OLS results, suggesting that the measurement error might be important. On the other hand, the proportional decline between the coefficients for NLSY79 and NLSY97 cohorts remains above 50% and is statistically significant.

The amount of financial compensation to participate in ASVAB was lower for the later cohort and could affect test performance through incentives and motivation.[15] We address these motivation effects on test performance using information on reason to take the ASVAB, which is recorded in the NLSY97. Respondents chose one of the following options:

[13] Further constraining the sample to include only respondents who were 16 years old and had completed the ninth grade at the time of the test delivers very similar estimates. These results are reported in table A8 in the online appendix.

[14] The SAT is a standardized test for college admissions in the United States. In the NLSY79, the SAT score is collected in 1980, 1981, and 1983 in the high school transcript survey, and it was available for 950 respondents. The majority of these individuals were expected to graduate high school in the survey year. In the NLSY97, SAT scores are also available in the transcript surveys of 1999–2000 and 2004 waves for 1,407 respondents who graduated high school or had reached 18 and were no longer enrolled.

[15] Respondents in NLSY79 were paid $50 (equivalent to $97 in 1997), and respondents in NLSY97 were paid $75.

Table 4
Returns to Schooling and AFQT, Standard Weights, 16 Years Old at Time of Test

	Men				Women			
	NLSY79 (1)	NLSY97 (2)	NLSY79 (3)	NLSY97 (4)	NLSY79 (5)	NLSY97 (6)	NLSY79 (7)	NLSY97 (8)
AFQT			.0894	.0317			.1299	.0451
			(.0203)	(.0191)			(.0236)	(.0171)
High school	.1387	.1916	.0834	.1705	.2538	.2332	.1604	.1975
	(.0433)	(.0442)	(.0453)	(.0465)	(.0464)	(.0282)	(.0474)	(.0301)
Associate's	.4076	.5662	.3237	.5374	.5097	.4728	.3855	.4131
	(.0890)	(.0866)	(.0852)	(.0882)	(.0768)	(.0611)	(.0799)	(.0671)
Bachelor's	.5341	.6986	.4119	.6508	.7476	.6979	.5726	.6310
	(.0649)	(.0580)	(.0701)	(.0629)	(.0698)	(.0447)	(.0739)	(.0515)
Master's	.6844	1.0505	.5227	1.0008	.5882	.9684	.4131	.8958
	(.1470)	(.1726)	(.1515)	(.1706)	(.2369)	(.1017)	(.2413)	(.1034)
R^2 (adjusted)	.2105	.2137	.2355	.2166	.2699	.2500	.3077	.2569
N	3,086	2,906	3,086	2,906	2,572	2,679	2,572	2,679

NOTE.—All statistics are weighted by the cross-sectional weights. Wages are inflation adjusted to 2007 using the CPI-U. Test scores are normalized to have zero mean and standard deviation one. Education variables: high school = 1 for high school graduates and 0 otherwise, associate's = 1 for individuals with an associate degree, bachelor's = 1 for bachelor's degree holders, and master's = 1 for individuals with a master's degree or higher. Other included controls: experience, experience^2, black, unemployment, metro status. For full results, see table A7 in the online appendix. Respondents are clustered at the primary sampling unit, and robust standard errors are reported in parentheses.

Table 5
Two-Stage Least Squares Using SAT Scores, Workers with 12 or More Years of Schooling

	Men		Women	
	NLSY79	NLSY97	NLSY79	NLSY97
OLS	.1588	.0611	.0760	.0436
	(.0448)	(.0285)	(.0308)	(.0282)
2SLS	.2158	.0992	.1926	.0547
	(.0557)	(.0433)	(.0445)	(.0448)
First stage results:				
SAT	.4588	.5097	.5182	.5104
	(.0155)	(.0133)	(.0132)	(.0128)
N	1,221	1,456	1,729	1,606

NOTE.—All statistics are weighted by the cross-sectional weights. Wages are inflation adjusted to 2007 using the CPI-U. Test scores are normalized to have zero mean and standard deviation one. Sample includes individuals with 12 or more years of schooling and valid SAT scores. Other controls: education dummies (see table 2 note), experience, experience^2, black, unemployment, metro status. For full results, see tables A9 and A10 in the online appendix. Respondents are clustered at the primary sampling unit, and robust standard errors are in parentheses.

(i) Because it's an important study; (ii) To see what it's like to take a test on a computer; (iii) To see how well I could do on the test; (iv) To learn more about my interests; (v) Family member wanted me to take it; (vi) To get the money; (vii) I had nothing else to do today. We split the NLSY97 sample into two groups, those who chose i–iv are the "motivated" group and those with v–vii are the "nonmotivated" group.[16]

Table 6 reports estimation results for each subgroup. The estimated test score coefficient is higher for the "motivated" group. We partly attribute this difference to measurement error in test scores. Test scores are likely to be less informative about the true cognitive ability of a respondent who puts lower effort into the test. This result may also suggest that there is a correlation between unobservable personal characteristics that affect both wages and the reason to take the test. However, including the motivation indicator as a control in equation (1) does not affect the estimated returns to schooling and cognitive skills (see table A12 in the online appendix). In table 6 the estimated return to cognitive ability is two to six times larger in the 1980s than in the 2000s for any subgroup. The differences are statistically significant at the 1% level. There is no statistically significant difference in the returns to schooling between the "motivated" and "nonmotivated" samples (see table A11 in the online appendix).

B. Estimation of Propensity Scores and Reweighting

We reweight the NLSY97 sample to match NLSY79 distributions of observable characteristics. To construct the weights, we follow the methodology developed in DiNardo, Fortin, and Lemieux (1996). We pool data from both surveys and use Probit models to estimate the probability that an observation is in the NLSY79, conditional on the variables of interest.[17] The estimated probabilities are used to construct the weights:

$$\psi(Z) = \frac{P(d1979|Z)}{1 - P(d1979|Z)},$$

where Z is the vector of variables of interest, $d1979 \in \{0, 1\}$ equals 1 when an observation is taken from the NLSY79, and $P(d1979|Z)$ is the conditional probability of appearing in the NLSY79 conditional on observable characteristics Z. The weight function, $\psi(Z)$, is used to reweight the observations in the NLSY97 to obtain nearly equal distributions of the variables of interest across the two surveys. Estimation results of equation (1)

[16] The results are not very sensitive to the division of individuals into subgroups. For example, estimating eq. (1) using only individuals who chose answer iv vs. those who chose answer vii provides very similar estimates.

[17] These probability estimations use sampling weights provided by the BLS to achieve population representative samples.

Table 6
Returns to AFQT, Standard Weights, Ordinary Least Squares, by Reason to Take the Test

	NLSY79	NLSY97		
	All	All	Motivated	Nonmotivated
Men:				
AFQT	.0956	.0328	.0464	.0162
	(.0088)	(.0079)	(.0105)	(.0125)
R^2 (adjusted)	.1661	.1535	.1753	.1351
N	25,491	12,458	6,445	5,743
Women:				
AFQT	.1078	.0624	.0645	.0571
	(.0077)	(.0079)	(.0095)	(.0140)
R^2 (adjusted)	.2257	.2713	.2865	.2488
	21,603	10,887	6,506	4,202

Note.—All statistics are weighted by the cross-sectional weights. Wages are inflation adjusted to 2007 using the CPI-U. Test scores are normalized to have zero mean and standard deviation one. Other controls: education dummies (see table 2 note), experience, experience^2, black, unemployment, metro status. See Sec.III.A for definitions of "motivated" and "nonmotivated" test-takers. For full results, see table A11 in the online appendix. Respondents are clustered at the primary sampling unit, and robust standard errors are reported in parentheses.

using the reweighted data are reported in tables A13 and A14 in the online appendix.

To reweight the NLSY97 by age we generate weights using $Z = (\text{age}, \text{age}^2, \text{age}^3)$. Table 1 reports summary statistics before and after the reweighting. Age reweighting has a small effect on the estimated returns to skills, return to ability declines substantially, and return to education increases between the 1980s and 2000s. We also construct a set of weights using a model that includes age variables, mother's and father's education, family income, intact family indicator, number of siblings, and an indicator for Hispanic origin. The results suggest that changing distributions of family characteristics do not explain the decline in returns to cognitive skills.

Finally, we test how the returns to cognitive ability and schooling would have changed if there was no shift in the distributions of industries and occupations over time.[18] We find that the effect of structural change on the estimates is relatively small for men and women.

IV. Wage Dynamics and Returns to Cognitive Skills

We estimate equation (1) and document a substantial decline in the return to cognitive skills and an increase in the return to formal education between the 1980s and 2000s. Here we estimate a dynamic wage specification, allowing for differential effects of education and ability by work experience.

[18] Many studies argue that structural changes in the labor market played an important role in the changing wage structure (see, e.g., Acemoglu 2002).

For each cohort, $T \in \{\text{NLSY79}, \text{NLSY97}\}$, we estimate

$$\begin{aligned} \ln \text{wage}_{it} = {} & \eta_1^T \,\text{EDUC}_i + \eta_2^T \,\text{ABILITY}_i \\ & + \eta_3^T \,(\text{EXP}_{it} \times \text{EDUC}_i) + \eta_4^T \,(\text{EXP}_{it} \times \text{ABILITY}_i) \\ & + \eta_5^T \,\text{EXP}_{it} + \eta_6^T \,\text{EXP}_{it}^2 + \eta_7^T X_{it} + \omega_{it}, \end{aligned} \tag{2}$$

assuming that the term ω_{it} has similar properties as ε_{it} in equation (1).

In the estimations of equation (2) the NLSY79 sample is weighted using the BLS sampling weights, and the NLSY97 sample is weighted using constructed weights to match the age distribution of the NLSY79. Table 7 reports the key results. Columns 1, 2, 5, and 6 report results obtained using equation (1), where schooling is defined as a continuous variable. These results are quite similar to those reported in table 2, and they show significant declines in the returns to cognitive skills over the 20 years and higher returns to education in the 2000s.

Columns 3 and 4 report estimation results of equation (2) for men. The coefficients η_3^T and η_4^T are lower (in absolute value) and not significantly different from zero in the NLSY97. Incorporating dynamics into the model reduces the coefficient on AFQT for NLSY79, η_2^{79}, and results in no significant difference between the returns to ability at entry wages in the 1980s and 2000s. Columns 7 and 8 report the results for women. Introducing wage dynamics into the model yields very similar returns to AFQT at entry wages across cohorts. The coefficient η_4^T is lower in the NLSY97, while the decline in returns to education with experience, measured by η_3^T, is more substantial in the 2000s. The results suggest that changing wage dynamics explain most of the decline in the returns to cognitive skills for men and women.

We interpret these findings within two alternative frameworks, which use similar empirical specifications, human capital accumulation theory and employer-learning theory. The human capital hypothesis, as in Ben-Porath (1967), suggests that ability may affect postschooling investments in human capital and that formal education may become obsolete over time. Within this theory, the coefficients in equation (2) are affected by changing technology and by structural changes in the labor market. The employer-learning theory posits that wages are determined by the expected value of the worker's productivity conditional on observable characteristics and past performance. In this framework, employee's education is an important initial signal to the employer about his or her potential unobserved productivity. As the worker accumulates experience in the labor market, the employer obtains more information on actual productivity and returns to schooling decrease while the returns to unobserved ability increase. Within this framework, changing estimates of equation (2) reflect changes in signaling and learning mechanisms.

Table 7
Dynamic Wage Equation, Ordinary Least Squares

	Men				Women			
	NLSY79 (1)	NLSY97 (2)	NLSY79 (3)	NLSY97 (4)	NLSY79 (5)	NLSY97 (6)	NLSY79 (7)	NLSY97 (8)
AFQT	.0768	.0300	.0248	.0254	.0913	.0701	.0721	.0603
	(.0090)	(.0113)	(.0147)	(.0224)	(.0078)	(.0105)	(.0135)	(.0160)
Education	.0715	.0931	.1023	.0905	.0814	.1000	.1117	.1388
	(.0038)	(.0067)	(.0074)	(.0134)	(.0037)	(.0058)	(.0077)	(.0091)
AFQT × experience			.0081	.0007			.0034	.0019
			(.0019)	(.0040)			(.0019)	(.0026)
Education × experience			−.0054	.0006			−.0060	−.0090
			(.0012)	(.0024)			(.0012)	(.0018)
Experience	.0521	.0597	.1392	.0473	.0496	.0273	.1530	.1960
	(.0065)	(.0118)	(.0187)	(.0417)	(.0064)	(.0083)	(.0189)	(.0308)
Experience^2	−.0011	−.0009	−.0028	−.0004	−.0018	.0001	−.0043	−.0050
	(.0005)	(.0011)	(.0005)	(.0016)	(.0005)	(.0006)	(.0005)	(.0011)
R^2 (adjusted)	.1727	.1697	.1750	.1697	.2264	.3096	.2291	.3179
N	25,491	12,458	25,491	12,458	21,603	10,887	21,603	10,887

Note.—NLSY79 statistics are weighted by the cross-sectional weights. NLSY97 statistics are weighted using weights constructed to match age distributions. Wages are inflation adjusted to 2007 using the CPI-U. Test scores are normalized to have zero mean and standard deviation one. Education measures completed years of schooling. Other included controls: black, unemployment, metro status. For full results, see table A15 in the online appendix. Respondents are clustered at the primary sampling unit, and robust standard errors are reported in parentheses.

In a conventional model of human capital accumulation, potential earnings increase with acquired skills and individuals allocate their time between work and on-the-job training. We rely on empirical findings by Veum (1993) and assume that cognitive ability makes workers more trainable and more able workers receive more training.[19] We also assume that technological change may affect investments in training. For example, Bartel and Sicherman (1998) use the NLSY79 data from 1987 through 1992 and find that production workers in manufacturing industries with higher rates of technological change are more likely to receive formal company training. Gashi, Pugh, and Adnett (2008) reach a similar conclusion using an administrative German data set.

To add formality to the discussion, assume in any period t that the stock of human capital, H_t, is given by $H_t = Q_t + (1 - \delta)H_{t-1}$, where Q_t denotes human capital produced in the current period t (investment) and δ is the depreciation rate. Formal schooling is denoted by H_0, which is the level of human capital upon entry to the labor market. A higher depreciation rate implies a faster depletion of formal and acquired on-the-job human capital. Human capital produced in the current period, Q_t, is assumed to positively depend on personal ability level, the current stock of human capital and technology.

Using this human capital framework, the coefficient on the interaction between education and experience in equation (2), η_3^T, picks up the depreciation of schooling and may also capture the complementarity between schooling and experience. Human capital investment and on-the-job training are reflected in coefficients on experience, η_5^T and η_6^T, and the interaction between ability and experience, η_4^T. The results in table 7 show a weaker relationship between the returns to cognitive skills and experience in the 2000s relative to the 1980s for men and women. This suggests that the role of on-the-job training declined over time. The 2000s results for men do not show a statistically significant decline in returns to education with experience: the interaction coefficient, η_3^T, is not different from zero, compared to -0.005 in 1980s. This suggests that the depreciation rate of formal schooling is lower in the 2000s or that the complementarity between schooling and experience increased over time. The increase in the coefficient on EXP^2 is also consistent with a declining depreciation rate in the 2000s. The results for women also show a weaker relationship between returns to ability and work experience in the 2000s but do not show an overall decline in the role of on-the-job training. On the other hand, female labor market and labor force participation went through many

[19] Rubinstein and Tsiddon (2004) also show that in times of rapid technological change, individuals invest more on the job. They also show that during such transitions innate ability contributes more to the wage growth within each education group than during times of a low rate of technological progress.

changes not captured by the simple specification of equation (2). We attribute the differences between male and female outcomes to developments in the labor market.[20]

We also examine the empirical findings in table 7 within the employer-learning theory. This theory argues that upon labor market entry worker's education conveys an important signal to the employer about his or her potential productivity. With labor market experience, as the employer gradually obtains more accurate information on the productivity of an employee, the return to schooling decreases and the return to unobserved ability increases.[21] Equation (2) is similar to the empirical strategy developed in Altonji and Pierret (2001), and our findings for the 1980s are comparable: the returns to ability increase with experience, and the returns to education decrease with experience. We find weaker evidence of employer learning in the 2000s: the returns to ability do not increase with experience for men and women. Within the employer-learning theory, these outcomes suggest that between the 1980s and 2000s there were advances in signaling about ability: in the 2000s employers obtain more information about employees' productivity from observing their formal education.

Within the human capital accumulation framework, the estimates are consistent with Nelson and Phelps's (1966) hypothesis, which posits that skills are most valuable when workers are adapting to a changing environment, but as the rate of technological change slows down, the relative productivity of formal education increases. A rapidly changing technological environment also implies a higher depreciation rate of human capital.[22] Within the employer-learning framework, the results are consistent with changing signaling and screening mechanisms associated with reforms in the education system following technological innovations.

Was technological change more rapid in the 1980s than in the 2000s? To obtain a measure of technological change, we follow the methodology that was proposed in Cummins and Violante (2002) and implemented in many

[20] Among many others, Blundell, Bozio, and Laroque (2011) document the changes over time in the labor market participation of men and women. For example, labor force participation of 27-year-old men in the United States was above 85% in both 1977 and 2007 and did not change much over time. For women these rates are around 55% and 70%, respectively.

[21] This theory was empirically tested by Farber and Gibbons (1996) and Altonji and Pierret (2001) using the NLSY79 data. Both studies argue that employer learning about workers' ability plays an important role in wage dynamics.

[22] This interpretation is also consistent with findings reported in panel B of table 3. Those with a bachelor's degree have around 7% higher return to AFQT than high school graduates in the 1980s, but there is no difference in the 2000s. Given that college graduates are more likely to receive training (see Veum 1993), the drop in the difference in the return to AFQT can be explained by the decline in training required to adapt to the changing work environment.

other studies. Cummins and Violante measure the speed of technical change for each capital good in equipment and software category (E&S) as the difference between the growth rate of constant-quality consumption and the growth rate of the good's quality-adjusted price. We use two measures of real equipment prices, National Income and Product Accounts (NIPA) official price index of E&S and the price of computers and peripheral (C&P) equipment.[23] Figure 2 shows a substantial decline in technical change in the 2000s. Average annual growth rates in the overall E&S indexes are 5%–7% in the 1980s and 1990s and drop to 1% in the 2000s. The C&P index grows by 19%–21% on average in the 1980s and 1990s and by 10% in the 2000s.

Prices reflect both consumption- and investment-specific shocks, as well as changing competitive conditions, and therefore only partially measure technological innovations. For example, Aizcorbe, Oliner, and Sichel (2008) decompose detailed semiconductor price indexes and show that swings in price-cost markups account for a considerable part of the price dynamics over the past 15 years.[24] However, their findings are weaker when using aggregate semiconductor prices, and they do not examine relative aggregate equipment and software prices or relative aggregate computer prices. We infer that relative aggregate price indexes are less susceptible to shocks associated with changing markups.

Existing literature offers more evidence on the changing pace of technological progress. For example, Goldin and Katz (2007) show that relative demand growth for college workers was more rapid in the 1980s but has slowed down since the 1990s. The authors conclude that technology has been racing ahead of education, especially in the 1980s.[25] Katz (2000) suggests that the maturing of the computer revolution led to the slowdown in growth of the relative demand for skill since the late 1980s. Greenwood and Yorokoglu (1997) argue that technological changes were more pronounced at the beginning of the 1980s. Hornstein, Krusell, and Violante (2005) show that at times of technological acceleration the average age of capital declines: firms scrap their machines earlier in response to a faster obsolescence rate.

[23] The NIPA official price index of E&S is not fully quality adjusted, although a significant effort has been made by the Bureau of Economic Analysis (BEA) to reduce the quality bias. The latter is a reliable constant-quality price index. We retrieve data from table 5.3.4. of the NIPA series. For further discussion on NIPA and BEA indexes, see Cummins and Violante (2002) and Bureau of Economic Analysis (2003).

[24] In contrast, Pillai (2012) uses growth of microprocessor performance (instead of semiconductor prices) and shows that it increased during the 1990–2000 period and decreased subsequently.

[25] Using National Science Foundation (NSF) data we document a similar trend in the proportion of R&D scientists and engineers in manufacturing companies. This proportion increased by 72% during the 1981–91 period and by 22% during 1997–2007.

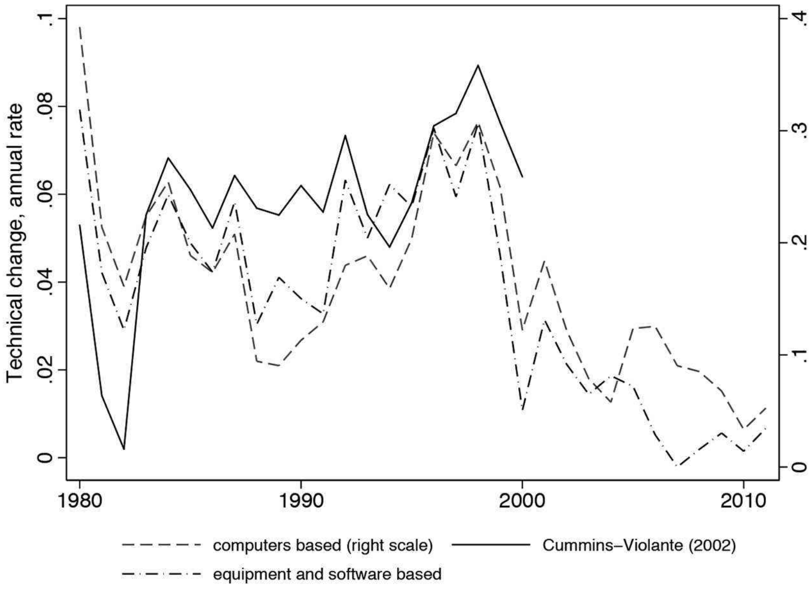

FIG. 2.—Aggregate measures of investment-specific technical change. SOURCE: Cummins and Violante (2002), www.econ.nyu.edu/user/violante/Journals/Cummins-Violante-Data.xls; National Income and Product Accounts.

Following their methodology and using data from the Bureau of Economic Analysis, table 2.10, we find that the average age of capital has increased from 8.5 years in the 1980s to more than 10 years in the 2000s, consistent with a slowdown in the rate of technological growth.

A changing technological environment not only leads to changes in training policies but also affects productivity signaling, screening, and monitoring mechanisms. Technological change was followed by reforms in the education system in terms of fields of study, implementation and development of new teaching approaches, and access to education. For example, McPherson and Schapiro (1998) document a positive trend in merit-oriented student aid policies, which provided higher-skilled individuals with opportunities to achieve more and higher-quality education. Kinsler and Pavan (2011) show that for higher-ability students, the effect of family income on the probability of attending a top-quartile school decreased significantly across the two waves of the NLSY. Castex (2010) and Lovenheim and Reynolds (2011) show that college nonattendance decreased substantially over time, particularly for high-ability students. Goldin and Katz (2007) argue that the increasing relevance of educational institutions to market needs starting in the late 1990s could have provided young workers with better skills for the jobs. Such adjustments in the education system should improve the screening process; that is, schooling degrees and grades immediately provide more accurate information on the true productivity of an individual in the 2000s than in the 1980s.

V. Conclusion

Returns to cognitive skills have declined by 30%–50% for men and women between the 1980s and the 2000s, while returns to formal education have increased. The changes in the returns are persistent across education groups, hold for different ability measures, and are robust in various specifications. Changing distributions of various observed characteristics (age and family background) and changing labor market structure cannot explain the decrease in the returns to cognitive ability between the 1980s and 2000s. Additionally, we examine potential biases associated with measurement errors in test scores and conclude that they do not explain the declining coefficients.

We examine the changes in skill prices over the 20 years in a dynamic wage model. We show that wage growth in the 1980s was positively associated with cognitive ability, but we do not find such a relationship in the 2000s. We analyze these outcomes within human capital accumulation and employer-learning frameworks. We show that the changes in wage dynamics, and therefore the overall decline in the returns to ability, can be attributed to the changing work environment and adoption of new technologies. We argue that more rapid technological growth in the 1980s raised the importance of on-the-job training and therefore raised returns to cognitive skills. In the 2000s, technological change has slowed down, leading to a more stable work environment. Within employer-learning theory, we argue that advances in signaling and learning about workers' productivity between the 1980s and 2000s can explain the changing wage dynamics. In particular, we conclude that employers obtain more information about employees' productivity from observing their formal education in the 2000s than in the 1980s.

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