Identifying the Effect of Ability and Schooling on Wages: Going beyond the NLSY

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Abstract

This paper estimates returns to education using US data. Using the NLS and NLSY79 (dataset) average wages for workers with different ability and educational levels can be estimated. Because of the high correlation between schooling and ability it is not possible to estimate across the entire ability-schooling support. The PUMS dataset (which includes wage and education data, but excludes ability) from the U.S. Bureau of the Census contains information that can be exploited to improve the precision of the NLSY79 estimates. The source of the improved precision is the non-parametric bounding technique described in Cross and Manski (2002). By incorporating the PUMS dataset, estimated returns to education at different ability levels are substantially sharpened. Results show a positive wage gap that does not increase over time for the most able during the 80's, and between 1980 and 2000.

Keywords: Schooling, Wages, Ability, Bounds, Identification Region
JEL Classification: J31.

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I. Introduction

In the 1980's, the United States experienced considerable changes in the structure of wages being paid to different demographic and educational groups. The most significant aspect of these changes is represented by the increase in the wages of more educated workers relative to their less educated counterparts (Katz and Revenga, 1989).

Several studies have attempted to explain the observed increase in education-related wage differentials. Commonly offered explanations have been associated with changes in the relative demand for workers at different educational levels. For example, changes in international trade patterns or in the industrial structure in the economy, or in the supply of workers of different educational attainments.

The cause of the widening gap has fundamental policy implications. If it is due to increasing returns to education over time, then there is justification for policies that enhance education. If it is due to an increasing return to ability over time, given that ability is more difficult to change through policy interventions, policy has a lesser role.

Earlier empirical studies on the increase in returns to schooling failed to take into account the effect of the underlying ability of individuals on wages. Recent studies suggest a relationship between a worker's inherent ability (i.e., ability not affected by acquisition of schooling measured by test scores) and his level of schooling. Moreover, this relationship may have changed over time. Thus, estimates of these increases are generally obtained from wage regressions that are potentially biased by the presence of unobserved ability in the wage-equation error.

Any of such changes in the schooling-ability relationship could have led to changes over time in the observed return to schooling. However, it is possible that the actual return to schooling has not changed over time, and that the observed increase in earnings differentials is attributable to changes in the correlation between schooling and ability.

Because of changes in the relationship between ability and schooling, the omission of ability as courtside in a wage regression has led to an "observed" rather than an actual increase in the return to schooling in the 1980's. A possible explanation is that the increase in the return to education has occurred largely for only certain workers, for example those with higher levels of "academic" ability.

However, it is not easy to disentangle the effect of ability and schooling in the available data. Workers with high ability tend to acquire a higher level of education. The sorting problem is that there is a strong positive correlation between ability and education. Therefore, both series are indistinguishable; it is not possible to estimate precisely the effect of schooling on wages for all levels of ability. For example, Table 1 shows that a few workers who have a college degree are positioned in the lowest quartile of ability. Given the small number of individuals, the effect of a college degree on wages of people at such an ability level cannot be reliably estimated. A problem of lack of observation is found in two dimensions: schooling and ability. I will be focusing on the identification problem that arises as a consequence of the strong positive correlation between these variables.

Table 1. Ability and Schooling
Age 35, (14 to 16 in 1979), White Males
N = 335

Highest Grade	Ability			
Completed	Quartile 1	Quartile 2	Quartile 3	Quartile 4
7	1	0	0	0
8	12	1	0	0
9	10	1	0	0
10	8	2	0	0
11	10	1	1	0
12	50	54	40	15
13	2	10	10	5
14	2	11	8	8
15	2	2	6	4
16	2	14	18	36
17	0	2	6	4
18	0	1	2	17
19	0	0	2	7
20	0	0	5	5

The main objective of this paper is to contribute to the identification of the effect of schooling on wages, for all levels of ability.

The majority of research about ability, schooling and wages uses the sample NLSY79 (National Longitudinal Survey Youth Cohort 1979)[1]. Given the small sample size of the NLSY (and the sorting problem), it is not possible to identify the effects of schooling on wages at all levels of ability. For example, Heckman and Vytlacil (2001) use the NLSY79, and find evidence that the effect of schooling on wages is not linear. However, they were not able to identify the effect of schooling on wages at all levels of ability, since the NLSY79 has fewer observations while considering some regions of the joint distribution of ability and education.

In order to solve this identification problem I will augment the NLSY79 information from a much larger dataset, that is the 1% PUMS (Public Use Microdata Sample)[2] from the U.S. Census. Although the PUMS does not capture the ability variable, it is added as a second sample, since a larger sample allows a sharper inference than the one obtained from the NLSY79 alone.

From the NLSY79 average wages for workers with different ability and education levels can be estimated. The PUMS dataset (which includes wage and education data, but excludes ability) contains information, which improves the precision of the NLSY79 estimates. The sources of the improved precision are the non-parametric bounding technique described in Cross and Manski (2002). Incorporating this marginal available form, the PUMS substantially sharpens the effects of ability and schooling on wages at different ability levels.

As a consequence of the use of PUMS as a second (and larger) database, there is an important reduction in the confidence intervals (around 30-40%). This sharper inference is equivalent to an increase in the sample size of 100%. Results also show a concentrated increase in returns among the most able. Essentially, this result is analogous to Herntein and Murray (1994).

The paper is organized as follows: Section 2) shows the evolution of wages overtime; Section 3) discusses the methodology; Section 4) presents the estimated results and section 5) concludes.

1 See Appendix
2 The sample size is 1% of the population.

II. Data

a) Ability

Following Spearman (1927), ability is defined as the first principal component called "g", a common factor that explains performance in each test of intelligence. A remarkable finding of the available literature is that only one combination of tests "g" predict performance almost as well as the full battery of test. (I am going to layout what is understood by ability and the assumptions I will make throughout).

Note that Spearman incorporates a specific factor called "s". The fact that test score increases with age and education indicates that scores would be measuring something more than ability. In order to sort this problem, something called "g" is taken as a measure of ability; it represents the principal components of the residual in a regression of test scores with respect to age and education at the moment tests were taken by youth.

Heckman and Vytlacil (1996) show that there is a little difference in terms of explained variability in wage regression using "g" or some other linear combination of tests.

b) Returns to education and ability for males

As in Heckman and Vytlacil (2002), in order to conduct a meaningful nonparametric analysis, I must limit the number of explanatory variables. To circumvent the curse of dimensionality, I include fewer variables than other papers that analyze wage, education and ability. Griliches (1976) shows that other variables, like family background and location, affect wages through schooling and ability, and they do not have any direct impact on the wage equation.

In order to have a significant variation on education and ability, I divide the population by considering three levels of schooling and ability. For schooling, I consider non-graduated high school individuals, those with a high school diploma and those with a college degree.

Figure 1 shows estimated changes in return to schooling overtime from the NLSY. This plot shows an increasing wage for college graduates, high school diploma holders those and non-graduated high school from the mid 80's to 2000. The most remarkable finding is the increasing log wages from mid 80's for college graduates. On the other hand, log wages for high school non-graduates started to increase only in the 90's. From the first figure we can infer that the increase in returns to education is greater for people with higher levels of education.

Hernstein and Murray (1994) claim that increasing returns to schooling education are heavily concentrated among the most able. Murnane, Willet and Levy (1995) conclude that ability had a larger impact on wages for 24 year-old men in 1986 than in 1978.

Figure 2 shows wage increases for all levels of ability. The raise in wages seems to be higher for the most able.

Moreover, Figure 3 shows an estimated increasing college wage gap starting in the mid 80's. There is a steady increase in the wage gap after the mid 80's. We can also observe a smaller increase in the wage gap between high school diploma holders and those non-graduated high school.

Following this perception, the most natural question would be: What happened to wages while considering different levels of education and ability? The strong correlation between schooling and education determines NLSY79 to have fewer observations in some regions of the joint distribution of education and ability (see Table 1). In particular, we cannot make inferences for non-high school graduated of high ability, and college graduates of low ability.

Somewhat unexpectedly, Figure 4 shows increasing wages for non-graduated high school holders with low ability. For high school graduates at the lowest ability level, we observe a wage increase only after 1992. Also, Figure 4 shows steady wage increase from the 80's in college graduates.

A feasible explanation of these results could be that wage increases with age (or experience), time, or maybe with both. Therefore in order to test which is the best specification it is necessary to introduce experience[3] and time effects.

Heckman and Vytlacil (2002) and Tobias (2003) show that the effect of time and age on wages are non linear. Therefore, there is the unacceptable and common practice of estimating linear wage equation against age and time as explanatory variables. A non parametric analysis with respect to age and time will be more convenient in this particular case. Having this in mind, I am going to estimate wages across education-ability cells, at a certain age and for a particular year. I will also estimate experience-time interactions.

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3 Because of the Miner critical distinction between experience and age, experience was used.

I formally test that the effect of ability on wages is nonlinear by estimating a regression with a dummy variable for ability in table 2.

Table 2		
Log Wages OLS Equation NLS80		
Ability - g - Dummy		
	Coefficient	**S.E.**
Constant	0.630	0.229
Schooling	0.062	0.009
Experience	0.077	0.025
Experience Square	-0.002	0.001
Dummy g Quartile 2	0.069	0.039
Dummy g Quartile 3	0.102	0.040
Dummy g Quartile 4	0.185	0.004

At the 95% level of confidence I reject that the dummy variables for the most able people and for those in the second quartile of ability is the same.

I also estimated the wage equation in a semi parametric way by using the NLS80. In particular I estimated the following equation:

$$Ln(W) = f(A) + \beta X + \varepsilon$$

Where W is the hourly wage, A is ability and X represents schooling and experience. I estimated this equation following Yatchew's (1998) method. Estimation results are shown in Figure 5.

The Yatchew (2003) specification test was also performed to test the null hypothesis that there is a linear relationship between the variables. This test is based on differencing two series in order to eliminate the non-parametric function. The statistic value obtained is 23, therefore I reject a linear effect of ability on wages.

Figure 6 shows college graduates – high school diploma holders wage gap for all ages for the most able. There is an increasing wage gap for white males between 25 and 33. This result that shows an increasing wage gap for the most able is consistent with Blackburn and Newmark (1993).

A problem arising while considering the use of NLSY79 is that the small number of observation in some region of the ability-schooling distribution makes it difficult to estimate wages at all levels of ability. In order to increase the number of observations for these regions I am going to use a second and larger database: PUMS.

III. Methodology

The objective of the empirical analysis is to estimate average wage given the level of ability and other control variables such as schooling, sex, race, experience and time. I am going to focus on time effects to account for the fact that the relationship between ability and schooling may have changed over time.

The effect of these independent variables is expected to be nonlinear, therefore I cannot pool observations and use ordinary least squares as a method of estimation. For example, the returns to education are different depending on sex and race. As in Heckman and Vytlacil (2001), I am going to conduct a nonparametric analysis; In order to accomplish this, I need to limit the number of explanatory variables.

The main objective is to estimate $E[\log(w)|x,a]$. Where w means wages, x represents sex, race, education, age and time; and a is ability. I am going to estimate time effect in 3 dimensions: schooling, ability and age (or experience)[4]; this allows us to measure the interactions between age and time.

NLSY79 is a sample from the probability distribution of wages given schooling and ability. I am able to estimate the return to education for people with high school degrees and low ability from NLSY79. In figure 4 we can observe decreasing wages in time. Also, I can estimate the wages for people with college degree and high ability. I need to see what happens with the wages of college graduates with low ability and with the wages for high school graduates of high ability.

NLSY79 has few observations in some regions of the joint distribution of ability and education. In particular, there is a small number of people with college degrees and low ability[5]. Because of that is not possible to estimate returns to education for all schooling and ability levels.

A possible solution for this identification problem is to augment the NLSY79 information to a larger dataset, like the PUMS. Although the PUMS does not capture the ability variable, its addition as a second, larger sample allows for sharper inference than is available from the NLSY79 itself.

4 Mincer emphasizes the use of experience rather than age.
5 This is called sorting bias.

NLSY79 allows us to estimate average wages for workers with different ability and education levels. The PUMS dataset (which includes wage and education data, but excludes ability) contains information that improves the precision of the NLSY79 estimates. The source of the improved precision is the non-parametric bounding technique described in Cross and Manski (2002). Incorporating this marginal information available from the Census substantially allows for better estimation of the effects of ability and schooling on wages, at different ability levels.

With the purpose of identifying the effects of education on wages at all levels of ability, I suggest to augment the NLSY79 information from a larger dataset, the PUMS. The PUMS has information about wages and education, the PUMS is a random sample from P(w,x). Although the PUMS does not capture the ability variable, its addition as a second, larger sample allows for sharper inference than is available from the NLSY79 alone. Inferences about E(w|x) can be made from the PUMS data, and an adding-up condition linking E(w|x) = to the parameters of interest, E(w|x,a), leads to sharper inferences (the marginal information is yielded by the PUMS data). I am going to determine whether or not efficiency gains afforded by the marginal information are substantial.

In conclusion, I am going to incorporate marginal information E(w|x) PUMS and E(a|x) from PUMS in order to improve inference about E(w|x,a).

I am going to make the following assumptions: i) I will divide the population into three levels of ability; ii) the data from PUMS will be population data.

In order to simplify the methodological exposition and for an intuitive understanding of the underlying methodology I will proceed to give an example of my process where ability is divided into two levels instead of three. [6]

We need to have in mind that P(w|x) is a mixture of two distributions:

- P(w,x,a=High)
- P(w,x,a=Low)

This marginal information places nonparametric bounds on E(w|x,a)

The lower bound for E(w,x,a=Low) is when Pr(a=Low|x)of the people have the lowest wage in the distribution of P(w|x). P(w|x,a=Low) is a right-truncated

6 The case with three ability levels is slightly more complex.

version of P(w|x) with the truncation at Pr(a=Low|x) of P(w|x) mass. The expectation of this distribution gives the lower bound on E[w|x,a=Low).

In a similar way I can construct an upper bound on E(w|x,a=Low).

Also, the vector { E(w|x,a=High), E(w|x,a=Low)} has to perform:

E(w|x) = E(w,x,a=High)Pr(a=High|x) + E(w|x,a=Low) Pr(a=Low|x)

The bound on { E(w|x,a=High), E(w|x,a=Low) } is a subset of a line in R^2. Cross and Manski (2002) term this the identification region.

Fig I. Identification Region

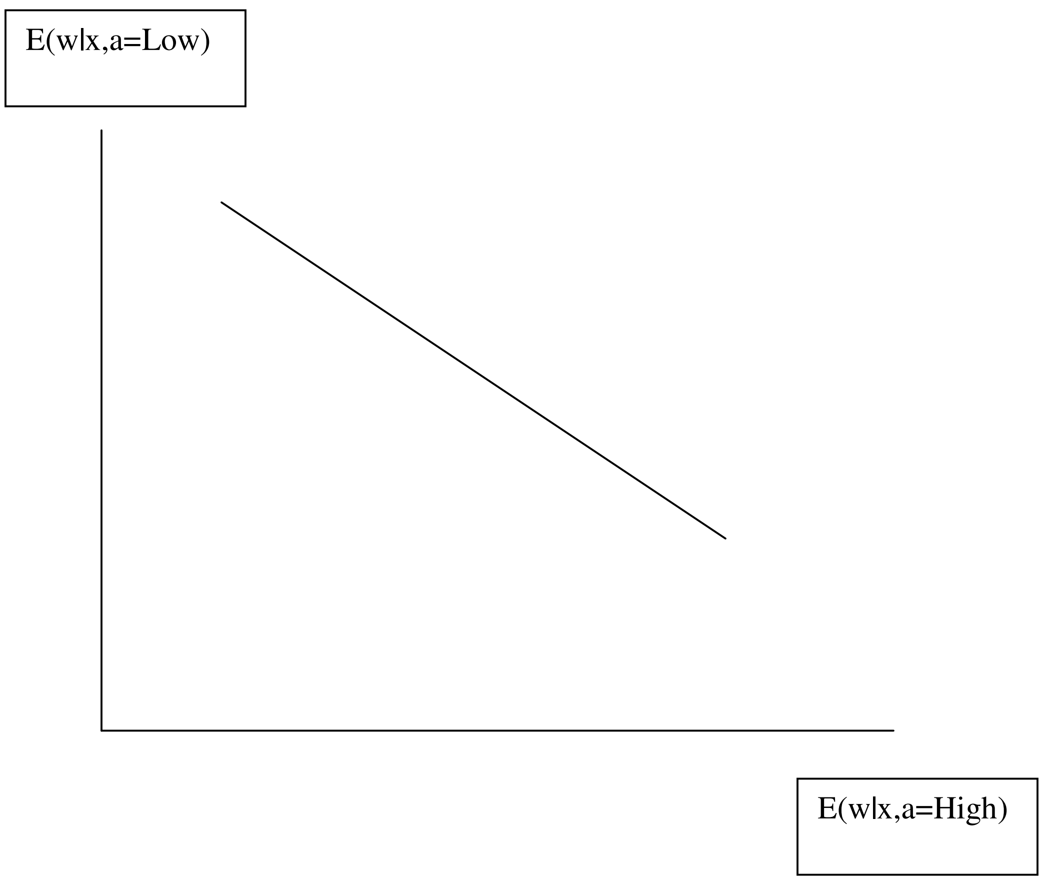
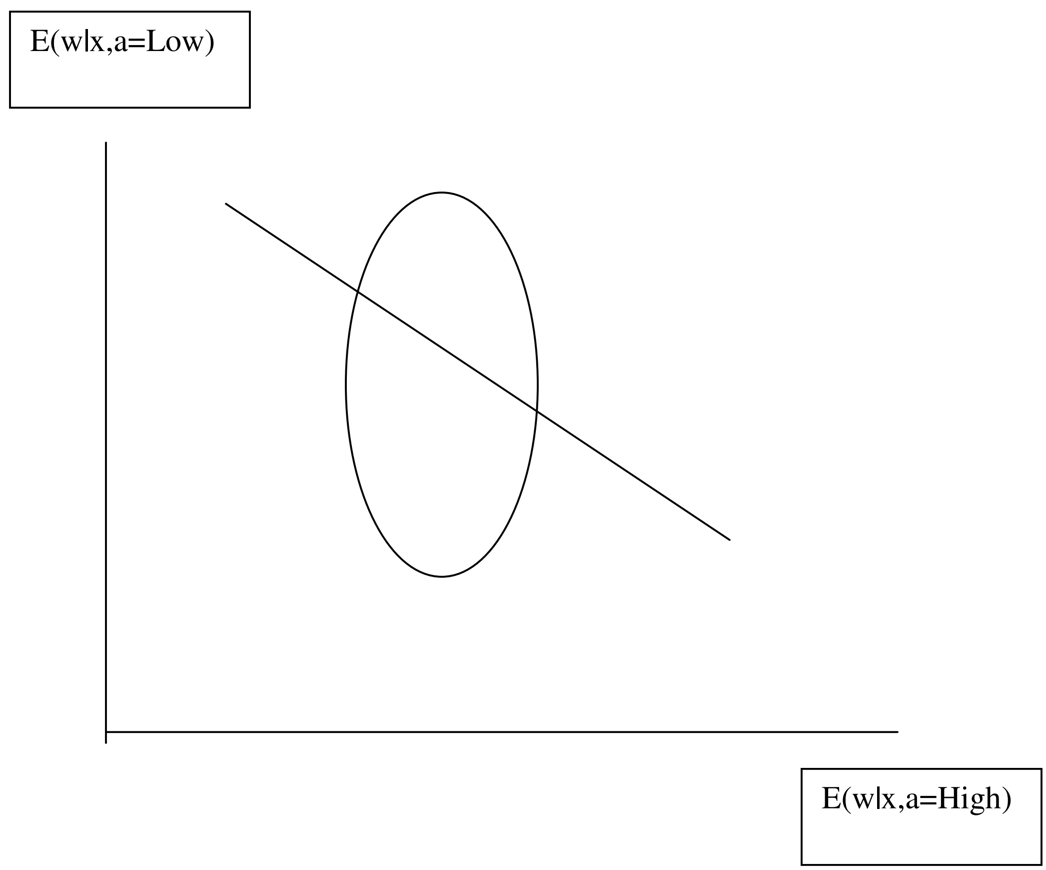


Figure II plots the lower and upper bound for the economic return to education for people with college degrees and low ability. This is a worst-case analysis, imposing no assumptions.

The next logical step is to combine these bound with information from NLSY79. I can combine the identification region estimated from PUMS with a (1-α)[7] confidence region for {E(w|x,a=High), E(w|x,a=Low)} from NLSY79. The picture II shows the gains in efficiency.

Fig. II. Sharper Inferences using PUMS bounds



The ellipse is the (1-α) confidence region for the two conditional expectations from the NLSY79.

7 α is the significance level.

IV. Estimation

Given the fact that I am going to use information from two different surveys, a direct concern is how close the NLS and NLSY79 matches the PUMS data[8].

Table 3 reports means and standard errors for the log of hourly wages by schooling for two periods (1980 and 1990) at two different ages (28 and 30). I report the statistics for the NLS and census data.

Table 3. Sample Means (and Standard Errors) of the Log of Hourly Wage (1980 dollars) by Age and Schooling.

	Age 30			
	NLS 1980	PUMS 1980	NLSY79 1990	PUMS 1990
Non-High School Graduates	1.75	1.80	1.65	1.87
	(0.09)	(0.02)	(0.07)	(0.05)
High School Graduates	1.94	1.94	1.89	2.02
	(0.07)	(0.01)	(0.04)	(0.02)
College Graduates	2.16	2.07	2.06	2.34
	(0.08)	(0.01)	(0.06)	(0.04)
	Age 32			
	NLS 1980	PUMS 1980	NLSY 1990	PUMS 1990
Non-High School Graduates	1.74	1.77	1.59	1.92
	(0.04)	(0.02)	(0.09)	(0.01)
High School Graduates	1.98	1.99	2.08	2.07
	(0.09)	(0.01)	(0.05)	(0.02)
College Graduates	2.36	2.45	2.39	2.46
	(0.09)	(0.01)	(0.10)	(0.04)

8 See Hellerstein and Imbles (1999) for a discussion of the NLS and PUMS surveys.

At first sight, we are able to observe that standard errors in the former survey are much lower; this could be explained by the higher sample size of the PUMS survey, and the higher attrition rate for the NLS survey. Secondly, according to Table 3, differences are more significant in 1990.

Table 4 presents the results for 1980. I will isolate the estimated wages from NLS, as well as information from PUMS that is used. The most remarkable fact is the important sharpening in the inferences. Also, because there are a small number of workers with college degrees and low ability we can't estimate economic return to education for that group. The use of the PUMS surveys allows for the estimation of a return between 1.91 and 2.20 at the 5% confidence level for the group with 6 to 10 years of experience and between 2.06 and 2.37 for individuals with higher experience.

Considering that the sample size for NLS is only 815, there is a significant improvement in the estimation. The average sharper reduction is equivalent to an increase of more than 100 of the sample size.

Table 4. Log Wages Bounds - 1980 -

6 to 10 years of experience						
Education Level	Ability	From NLS		Using PUMS		Reduction in Confidence Intervals (%)
High School	Low	1.79	2.68	1.79	2.01	75.8
High School	Middle	2.04	2.39	2.04	2.26	36.4
High School	High	1.77	2.23	1.77	2.14	21.2
College	Low			1.91	2.2	-
College	Middle	2.1	2.42	2.1	2.25	53.4
College	High	2.22	2.4	2.22	2.4	0
11 to 16 years of experience						
Education Level	Ability	From NLS		Using PUMS		Reduction in Confidence Intervals (%)
High School	Low	1.93	2.12	1.93	2.12	0
High School	Middle	2.04	2.23	2.04	2.23	0
High School	High	1.97	2.25	1.97	2.14	37.7
College	Low			2.06	2.37	-
College	Middle	2.36	2.65	2.36	2.60	15.8
College	High	2.32	2.58	2.32	2.58	0

Table 5 presents the results when information from NLSY79 is used.

The sample size of the NLSY79 is more than three times the size of NLS, because of that we don't observe significant reduction in the confidence interval width. However, what is useful about this study is that I am able to estimate a bound for the economic return of people with college degrees and low ability.

Table 5. Wages Bounds – 1990 - 6 to 10 years of experience					
Education Level	Ability	From NLS79		Using PUMS	
High School	Low	1.66	1.76	1.66	1.76
High School	Middle	1.85	1.99	1.85	1.99
High School	High	1.83	2.03	1.83	2.03
College	Low	-	-	1.40	2.18
College	Middle	1.84	2.11	1.84	2.11
College	High	2.17	2.36	2.17	2.36

Table 6 presents the results for the most recent year with NLSY and PUMS data: 2000.

Because of the structure of the panel data, as people's experience (or age) increases with time, we don't observe individuals with low levels of experience in the 2000 sample. Therefore it is only possible to analyze individuals with more than 11 years of experience.

Table 6. Log Wages Bounds - 2000 - 11 to 16 years of experience						
Education Level	Ability	From NLS		Using PUMS		Reduction in Confidence Intervals (%)
High School	Low	1.70	2.12	1.70	2.12	0
High School	Middle	1.66	2.19	1.66	2.19	0
High School	High			1.53	2.10	-
College	Low			2.37	2.36	-
College	Middle	2.25	2.62	2.25	2.54	22.1
College	High	2.49	2.69	2.49	2.69	0

In table 7, I reject the hypothesis of an increasing wage gap only for the most able during the 80's for the individuals with 6 to 10 years of experience.

Table 7: Wages and Wage Gap by Schooling-Ability. 1980 -1990

6 to 10 years of experience

Education Level	Ability	1980 Wage Bound		1990 Wage Bound		1980 Wage Gap	1990 Wage Gap	1990 with respect to 1980 Wage Gap Increase
High School	Low	1.79	2.01	1.66	1.76			
High School	Middle	2.04	2.26	1.85	1.99			
High School	High	1.77	2.14	1.83	2.03			
College	Low	1.91	2.20	1.40	2.18	0	0	0
College	Middle	2.10	2.25	1.84	2.11	0	0	0
College	High	2.22	2.40	2.17	2.36	+	+	0

Similarly, we observe a positive wage gap for the most able for the years 1980 and 2000 for people with more than 11 years of experience. Therefore, there is no indication of an increasing wage gap overtime.

Table 8: Wages and Wage Gap by Schooling-Ability. 1980 -2000

11 to 16 years of experience

Education Level	Ability	1980 Wage Bound		2000 Wage Bound		1980 Wage Gap	2000 Wage Gap	2000 with respect to 1980 Wage Gap Increase
High School	Low	1.79	2.01	1.70	2.12			
High School	Middle	2.04	2.26	1.66	2.19			
High School	High	1.77	2.14	1.53	2.10			
College	Low	1.91	2.20	2.37	2.36	0	0	0
College	Middle	2.1	2.25	2.25	2.54	0	+	0
College	High	2.22	2.40	2.49	2.69	+	+	0

Counterfactual Policy Exercise

In this section I am going to address the estimation of economic returns to education over time in an alternative way because it is potentially useful for policy implications.

One possible policy is to increase the resources assigned to grants and loans in order to promote college education for people with low incomes or with financial constraints. As I mentioned, earlier it is relevant to evaluate the impact of such a policy.

In particular, the following hypothetical policy-oriented question is posed: What would be the economic returns to education by schooling if there were an increase in the number of people with college degrees and high ability (explained by an increase in the number of people with college degree)? I will hypothesize that only individuals with both a high school diploma and high ability also have a college degree.

In order to answer this question, I assume that the long regression on wages given schooling and ability is constant; therefore this regression remains unchanged under the new distribution of people by schooling levels. Instead, there is a change in the short run regression of ability given schooling.

In this paper, ability refers specifically to cognitive ability. Therefore, it is not possible to modify through policy interventions. However, I can write the probability distribution of ability given schooling according to Baye's rule in the following way:

$$\Pr(Ability = A_i \mid Schooling = S_i, X) = \frac{\Pr(Schooling = S_i \mid Ability = A\ \ , X) * \Pr(Ability = A_i \mid X)}{\Pr(Schooling = S_i \mid X)}$$

It is possible to do policy interventions that change the distribution of schooling given ability[9], and in this way we can change the distribution of ability given schooling.

The objective of this exercise is to change the probabilities from the identification region and estimate their impact on wages.

Table 9 presents the estimation results.

9 Grants, loans, etc.

Table 9. Policy Exercise. 10% increase in the share of people with college degree and high ability				
6 to 10 years of experience				
Educational	1980		1989	
Level	Wage	Bound	Wage	Bound
High School	2.09	2.20	1.45	2.11
College	1.61	2.51	2.18	2.22
11 to 16 years of experience				
	1980		2000	
	Wage	Bound	Wage	Bound
High School	2.21	2.35	1.35	2.54
College	2.45	2.47	2.54	2.57

As in the previous section, I can conclude that there is a positive college degree – high school degree wage gap. If we increase the number of people with college degree and high ability in the population we observe a positive wage gap. However, I cannot say that the wage gap is increasing over time.

IV Conclusion

The result of the estimation shows that returns to education are concentrated among the people with the highest ability. We observe a positive college degree - high school diploma wage gap only for individuals with the highest ability. This result is consistent with the claim of Hernestein and Murray (1994) who found that returns to education are concentrated among the most able.

An increasing wage gap during the 80's is also rejected for individuals with medium experience, and between 1980 and 2000 for individuals with higher experience.

Data Appendix

The NLS is a sample of 815 workers that contains information about wages, schooling and an IQ test.

The NLSY79 is a sample of 7429 white youth who where between ages 14 and 22 during the first year of the survey, 1979 (3709 males and 3720 females). They were interviewed yearly until 1994, and every two years after that. The data takes advantage of scores on the ASVAB test (Armed Services Vocational Aptitude Battery). These are several tests measuring academic (or cognitive) and mechanical ability (arithmetic, numerical operations etc). These test scores are used as (potentially error-prone) measures of ability.

In order to deflate wages data, I use the national consumption expenditure deflator. Also, because of the presence of outliers, I restrict the sample to those receiving an hourly wage higher than 50% of the minimum wage in 1980.

The PUMS survey is a 1% census sample from 1980, 1990 and 2000. The number of observations is more than 200,000.

Bibliography

Blackburn, McKinley, and David Neumark. 1993 “Omitted-Ability Bias and the Increase in the Return to Schooling’ Journal of Labor Economics, 11: 521-544.

Cross, Philip, and Charles Manski. 2002. “Regressions, Short and Long Run”. Econometrica, 70 (1): 357-368.

Grogger, Jeff, and Eric Eide. 1995. ”Changes in College Skill and the Rise in the College Wage Premium” Journal of Human Resources, 30(2): 280-310.

Heckman, James, and Edward Vytlacil. 2001. “Identifying the Role of Cognitive Ability in Explaining the Level of and Change in the Return to Schooling”. Review of Economics and Statistics, 83 (1):1-12.

Hernstein, Richard, and Charles Murray. 1994. “The Bell Curve” New York: Free Press.

Katz, Lawrence and Murphy, Revenga, Kevin (1992). “ Changes in Relatives Wages: 1963-1987: Supply and Demand Factors. The Quarterly Journal of Economics. Vol 107. No 1: 35-78.

Manski, Charles and John Pepper. 2000. “ Mototone Instrumental Variables: With an Application to the Return to Schooling” Econometrica, 68(4): 997 -1010.

Murnane, Richard, John Willett, and Frank Levy. 1995. “The Growing Importance of Cognitive Skills in Wage Determination” The Review of Economics and Statistics, 77 (2): 251-266.

Tobias, Justin. (2003) “Are Returns to Schooling Concentrated Among the Most Able? A Semiparametric Analysis of the Ability-earnings Relationships”. Oxford Bulletin of Economics and Statistics 65(1): 1-29.

Yatchew, Adonis. (1998) “Nonparametric Regression Techniques in Economics”. Journal of Economic Literature , XXXVI, 669-721.

Yatchew, Adonis. (2003). “Semiparametric Regression for the Applied Econometrician”. Cambrdige University Press.

Figure 1.a) Log Wages by Schooling

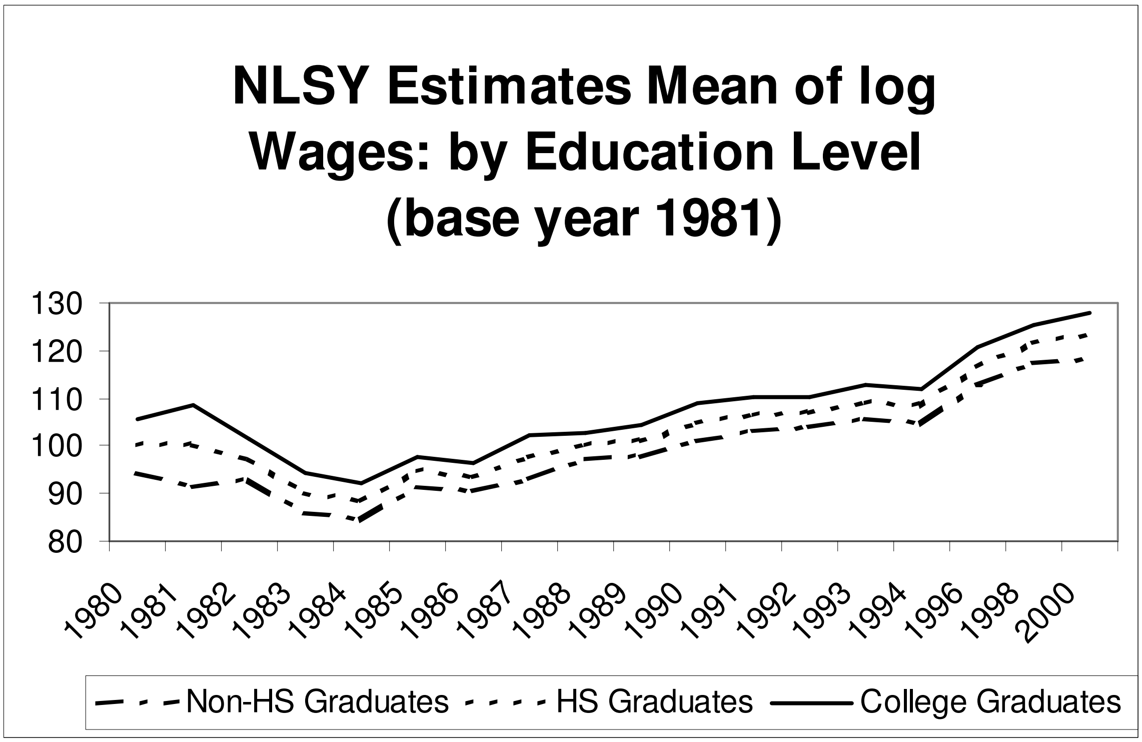
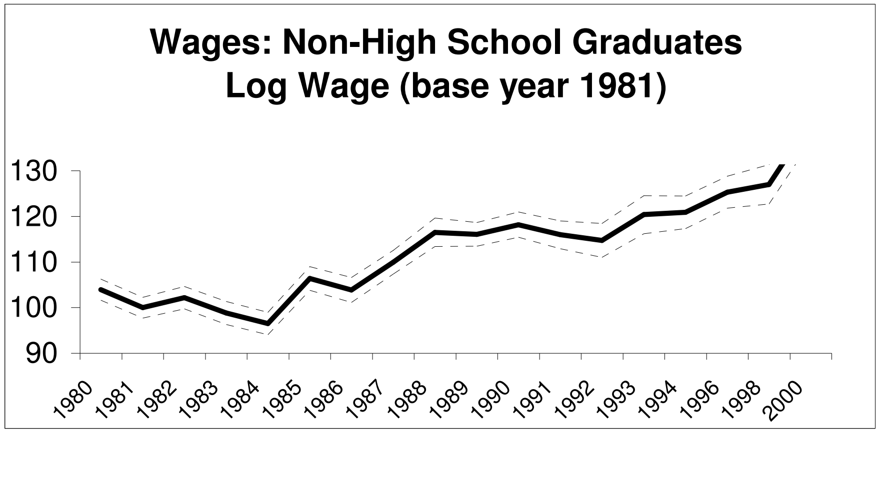
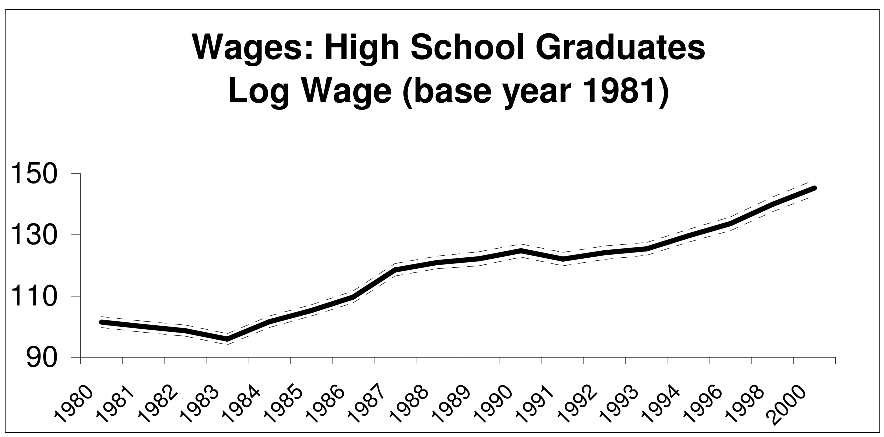


Figure 1.b) Log Wages by Schooling





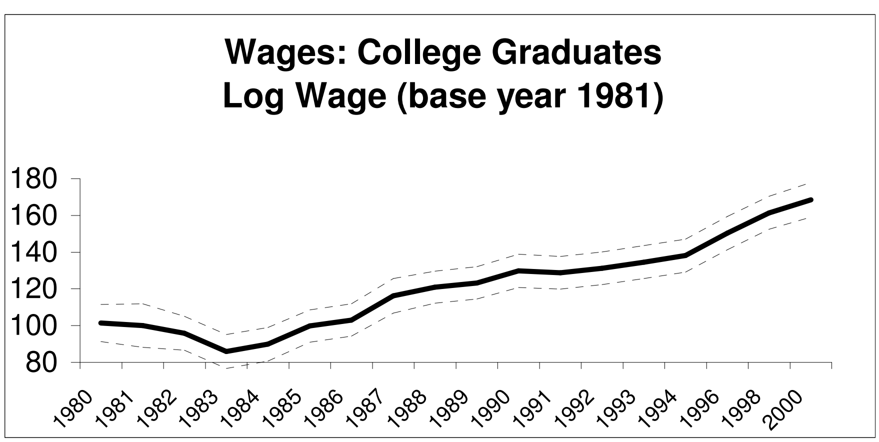


Figure 2.a) Log Wages by Ability

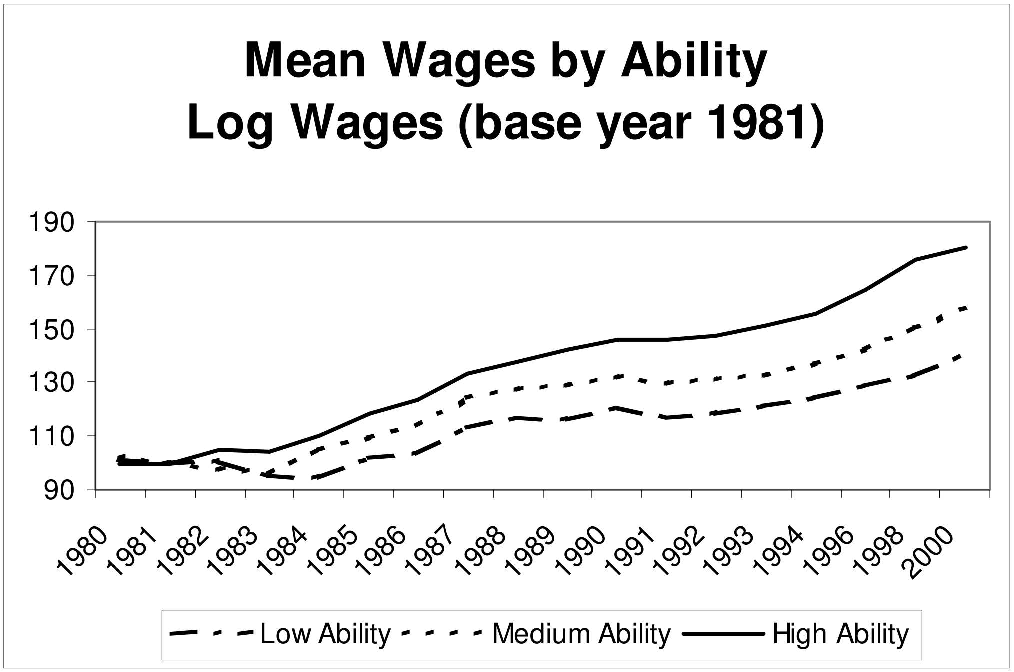


Figure 2.b) Log Wages by Ability

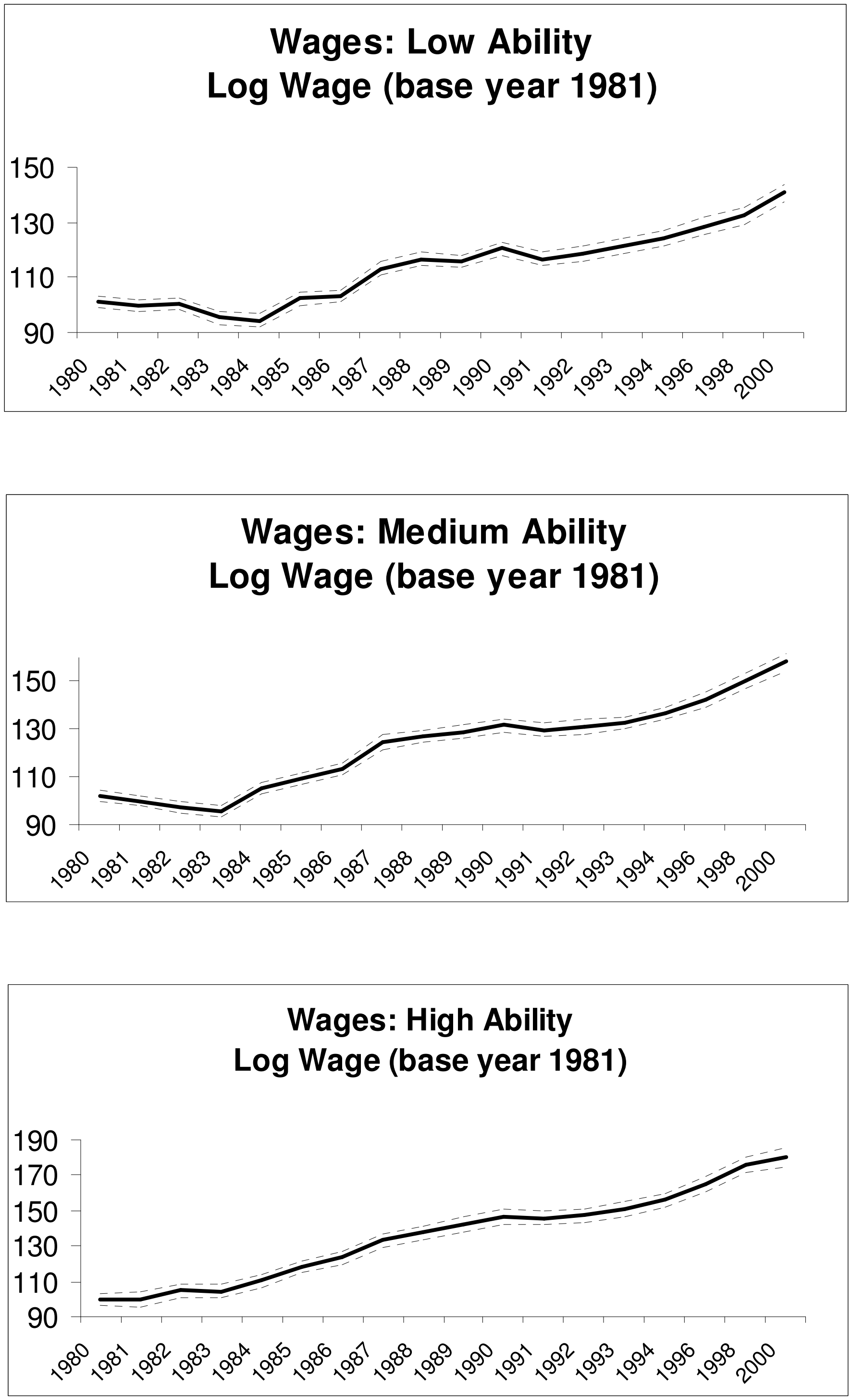
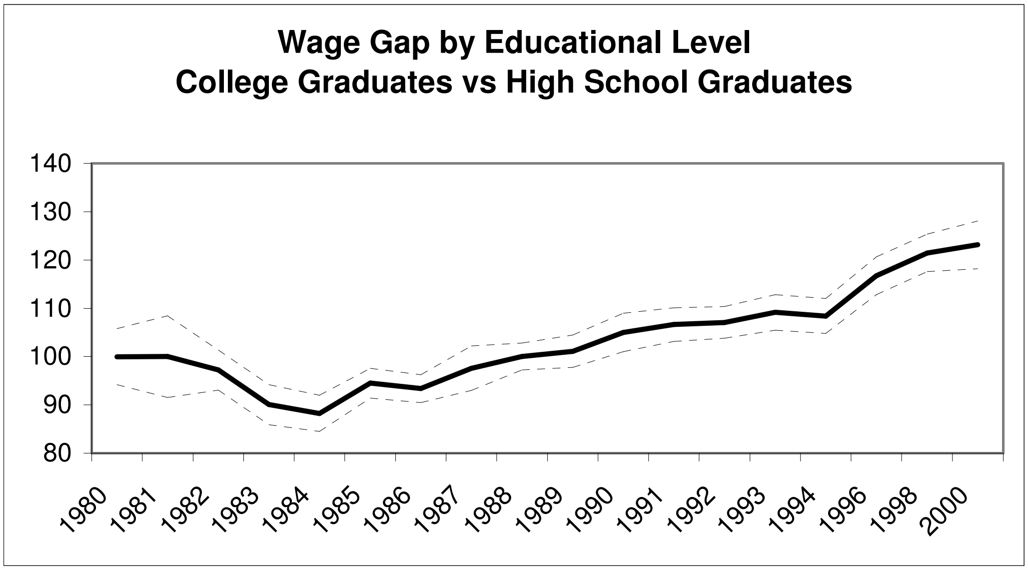


Figure 3. Wage Gaps



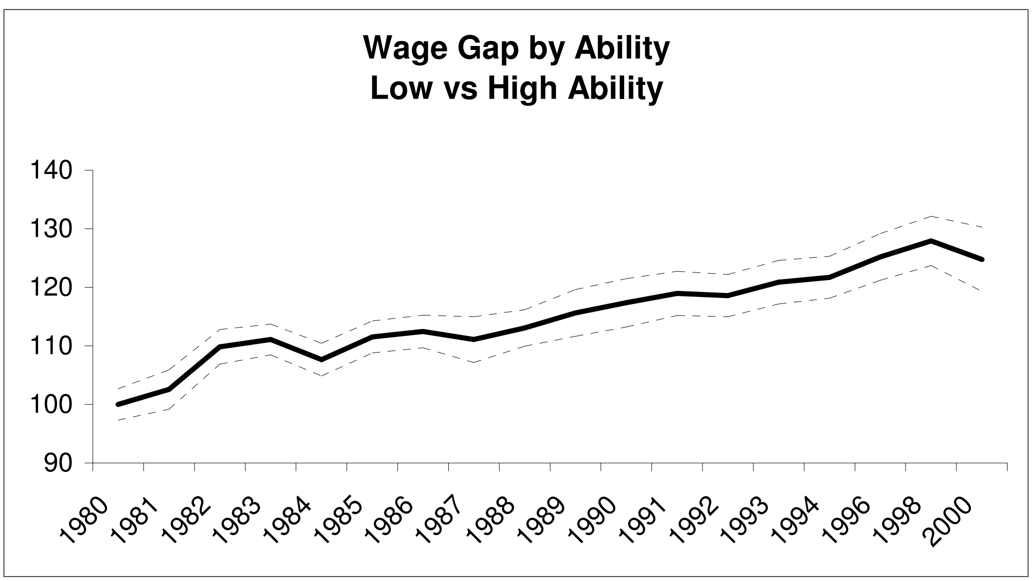
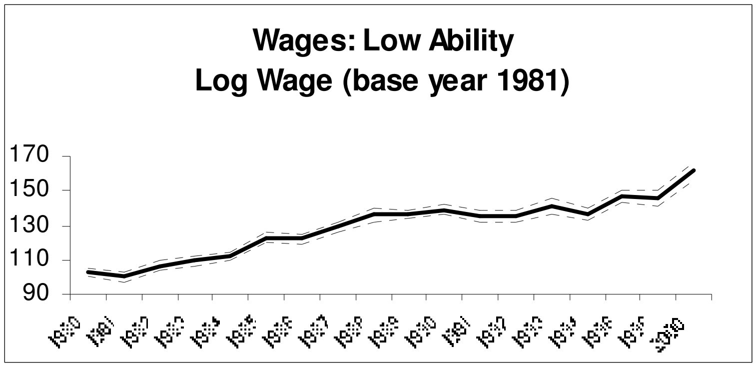


Figure 4.a. Wages for Non-High School Graduates by Ability



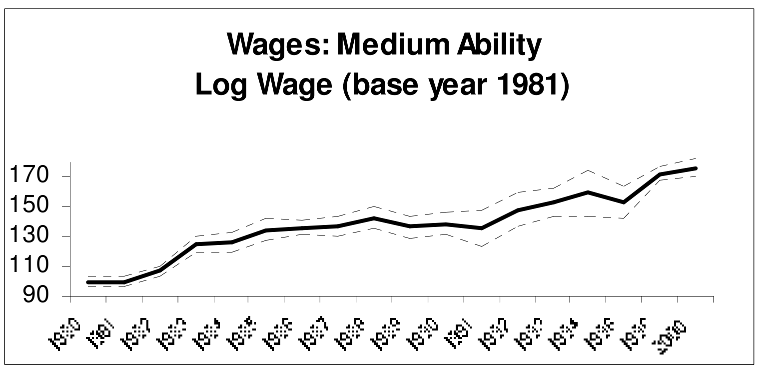
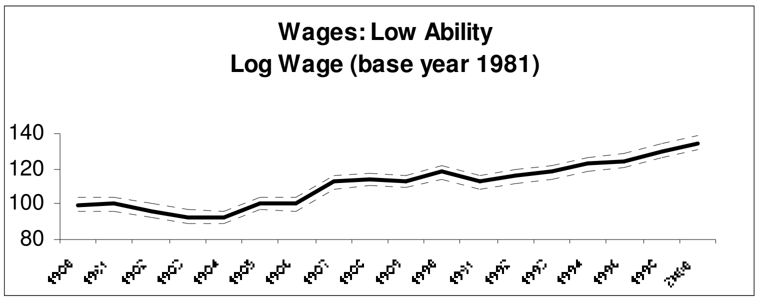
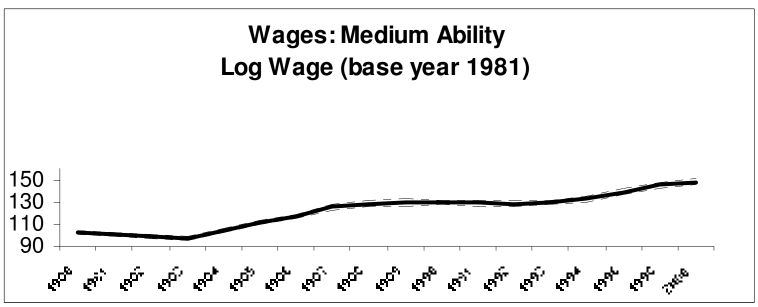


Figure 4.b. Wages for High School Graduates by Ability





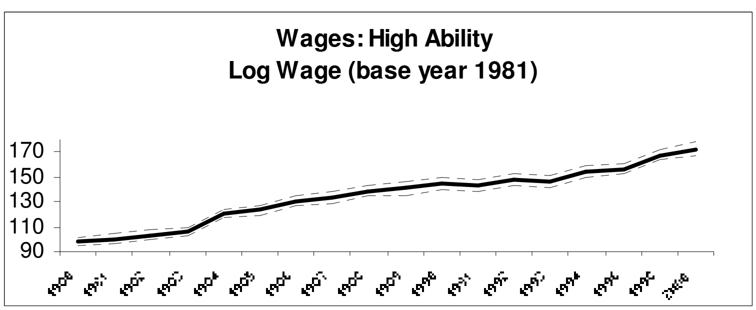
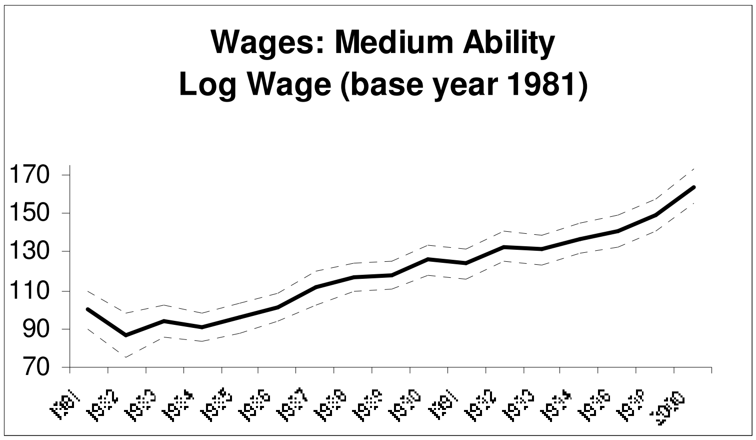


Figure 4.c. Wages for College Graduates by Ability



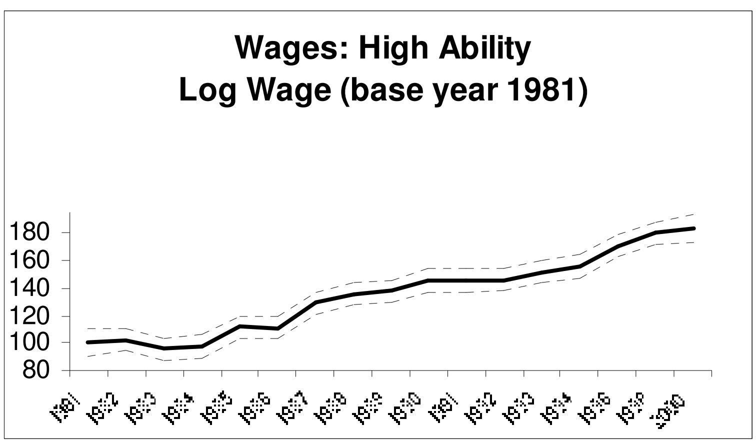


Figure 5: Impact of Ability on Log(Wages)

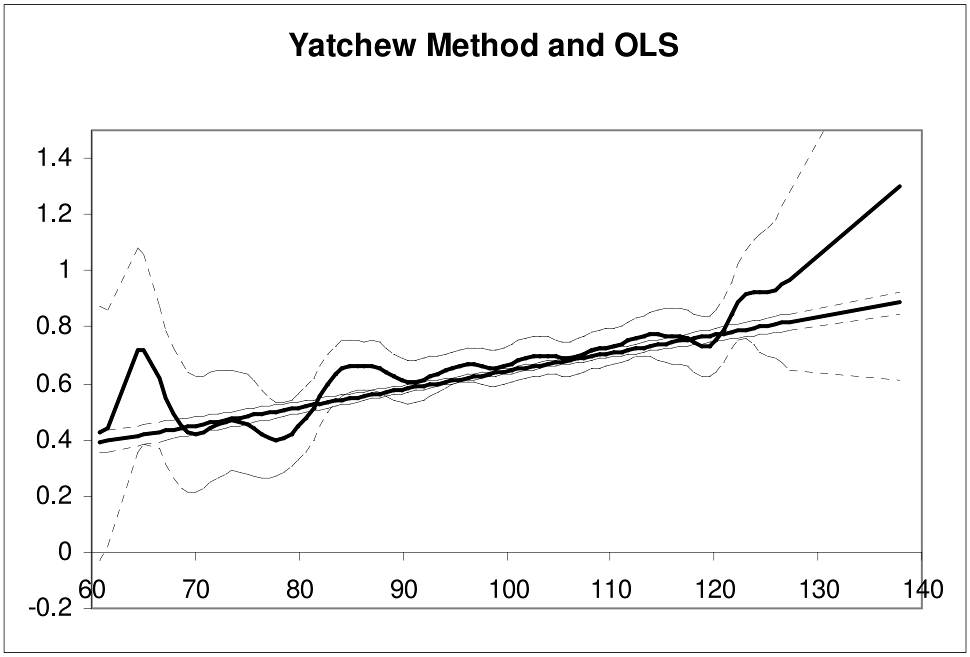
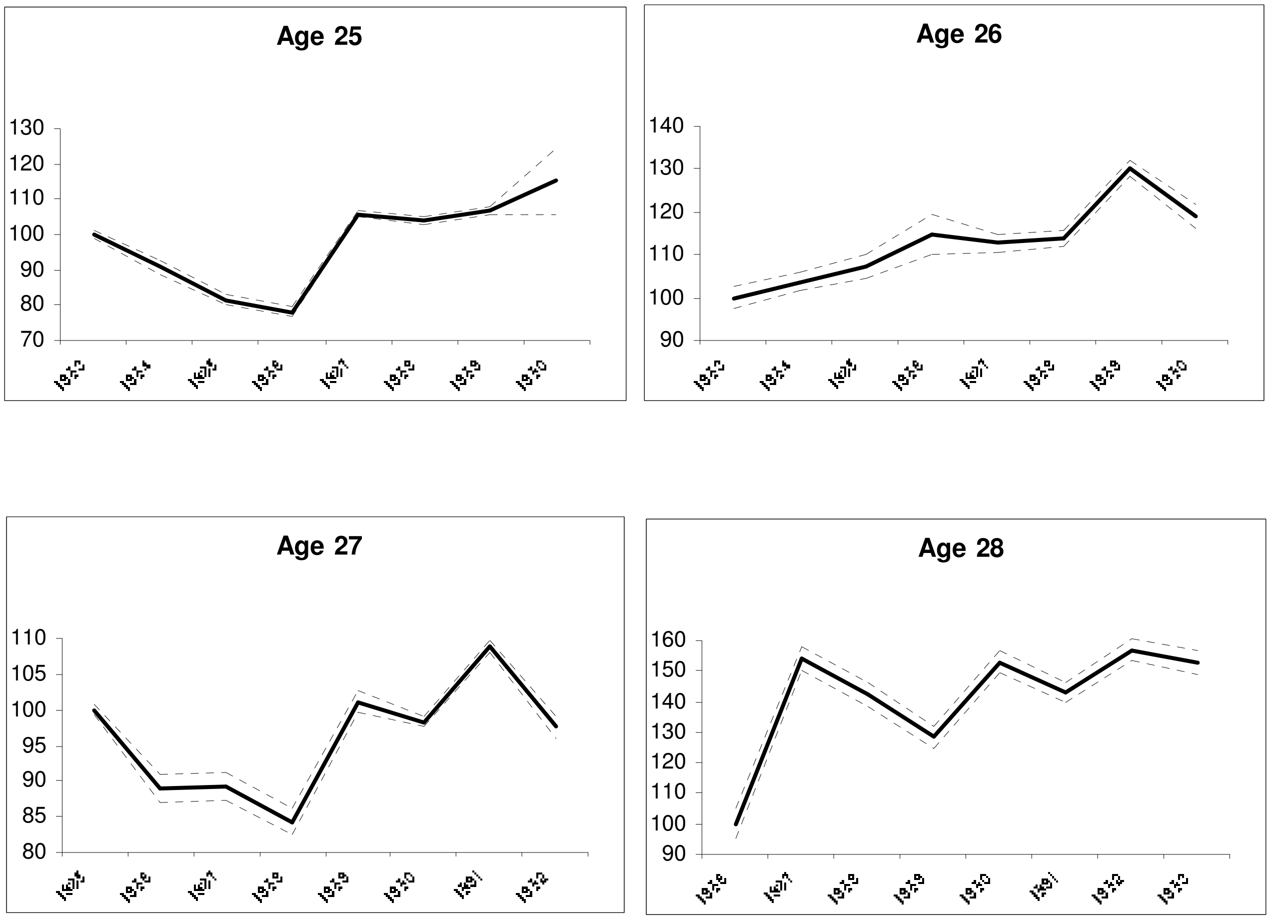
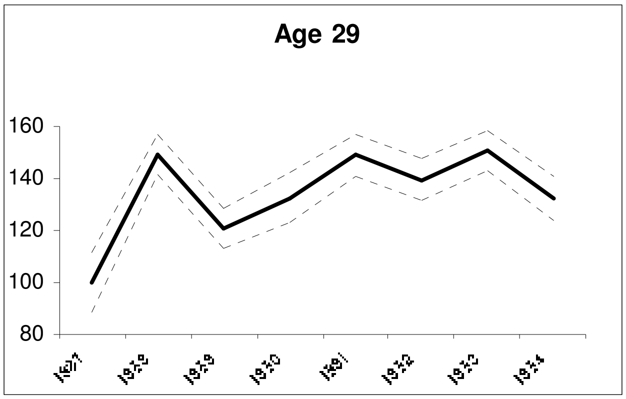


Figure 6. Wages: College-High School Wage Gap Highest Ability. By Age.

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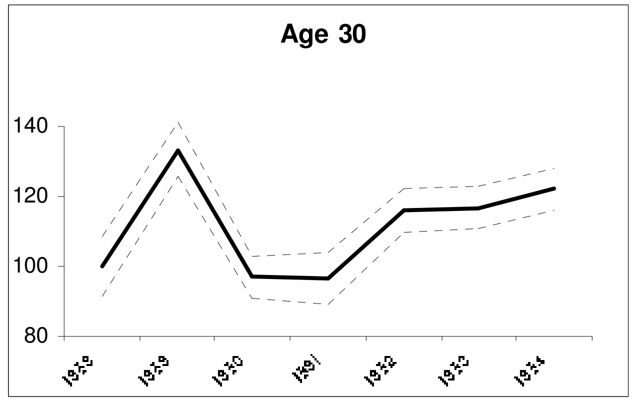
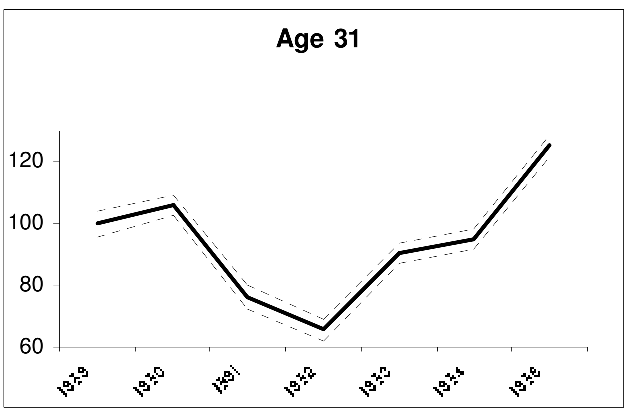
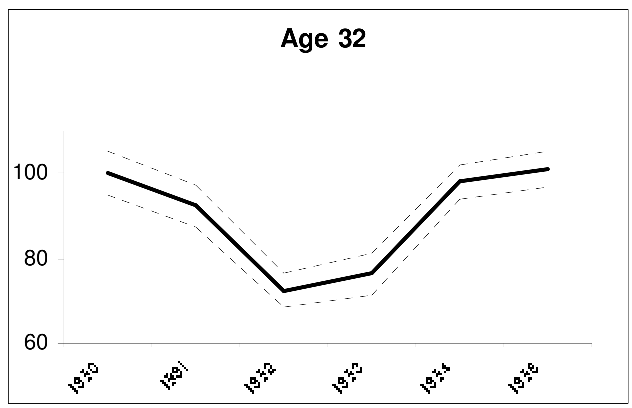
140
120
100
80


Age 30
140
120
100
80


Age 31
120
100
80
60


Age 32
100
80
60