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Returns to Schooling: A Quantile Regression

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Abstract

This paper contributes to the large body of economic literature that attempts to estimate the returns to schooling. It uses quantile regression to estimate the effect of an additional year of education on monthly wage for earners in different quantiles. Using data from the young men's cohort of the National Longitudinal Survey, the paper attempts to control for ability, family background, geography, and race, and finds that the returns to schooling is approximately 3.49% for men. Furthermore, the paper finds that while the effect of education on earnings is not significantly different from quantile to quantile, the significance of education increases with earnings.

Introduction

This paper builds on previous economic research analyzing the returns to schooling by utilizing a quantile regression method to estimate the returns to schooling for different levels of income. It attempts to control for ability with IQ test scores and includes measures of father's and mother's education to control for family effect.

The motivation for this paper is simple. A rational economic actor deciding to take on an additional year of school makes this decision by weighing the cost of attending school now against the present value of the expected future return of this additional year of investment in human capital. If the effect of education on earnings is significantly different for different earnings quantiles, this affects a person's decision to attend college.

It may make more sense for a student who wishes to become a high school instructor, for example, and make a maximum salary of about $50,000 to not continue past 16 years of schooling. If wages in the $50,000 range are as dependent on education as experience, for example, then it makes more sense to defer further education in exchange for work experience, all else equal. If a student wishes to become a financier and earn a salary, for example, of up to $150,000 or $200,000, he may decide to continue past 16 years of schooling because earnings in that range may be more sensitive to additional educational attainment.

To investigate this idea, the paper will first review previous literature examining the returns to schooling before presenting the quantile regression model in the "Model" section. The model will be followed by a short description of the data. Here, the paper will also discuss heteroskadasticity, outliers, non-normality of wages, as well as the advantages of quantile regression given these data conditions. Afterward, the paper will present the results of the regression, discuss them, as well as discuss potential shortcomings of the model. The paper will conclude with an estimate of the returns to schooling and a discussion of where this estimate falls within the range of previous estimates presented in the literature review.

Literature Review

Previous research analyzing the returns to schooling seem to be largely concerned with accounting for unobserved affects (i.e. ability) and resolving heteroskadasticity issues. Both are significant problems since endogeneity biases the estimated coefficients while heteroskadasticity increases the probability of making a type I error. Previous research usually deals with heteroskadasticity by taking the log of the dependent variable and producing robust standard errors. As we will see, logging the dependent variable does not significantly solve non-normality issues with the dependent variable. The various methods of dealing with endogeneity are more interesting.

Angrist and Kreuger, for example, use compulsory schooling attendance laws as instrumental variables to solve the endogeneity issues (Agrist and Kreuger, 1990). They observe children with the same age and ability who have acquired different levels of schooling because they were born either before or after the cutoff date for school enrollment in a given year. This birth, before or after the cutoff, serves as an exogenous source of variation, which is both uncorrelated with error and correlated with schooling. It also theoretically only affects earnings through education. They estimate the returns to schooling to be about 7.5%.

Another study utilizes a similar method to analyze the returns to schooling in Indonesia (Duflo, 2000). It uses government mandated school construction as an exogenous source of increase in schooling. This IV approach estimates the return to schooling to be anywhere from 6.8% to 10%.

Taubman published an analysis studying identical twins (Taubman, 1976). By studying only identical twins, Taubman hoped to control for ability and, therefore, avoid an education variable, which was correlated with the error term. He estimated returns to education to be roughly 3%. Similar studies concluded that ability differences account for most of the earnings gap between the highly educated and less educated. Later studies by Ashenfelter, Orley, and

Kreuger also analyze identical twins and conclude that the return to schooling is about 15% (Ashenfelter, Orley and Kreugaer, 1994).

One of the theoretical difficulties with using identical twins is the fact that identical twins have different levels of education in the first place. As stated in the introduction, a rational economic actor weights the cost of attending school against the *present value* of the investment's expected future returns. However, this implied that individuals discount this benefit at some rate, r. Ceterus Paribus, the fact that identical twins make different schooling decisions implies that identical twins have varying discount rates and, therefore, are not so identical (Borjas, 2010). All else equal, a twin who quits school earlier than his counterpart discounts the returns to education at a higher rate.

It is because of this theoretical difficulty that this paper uses IQ scores to capture unobserved ability and avoid endogeneity. While IQ tests are questionable, it is the best available measure of ability and significant at the 1% level in the standard OLS regression in this paper.

Heteroskadasticity is still an issue, but quantile regression largely eliminates these concerns since it is insensitive to biases in the conditional mean of the dependent variable. These benefits will be discussed further in the next section.

The most beneficial product of this literature review is a range of estimates from dependable and reputable studies. Given these studies, it is expected that our estimate should fall somewhere between 3% and 15%.

Model

The proposed model will take the form:

$$\log(W_Q) = X_Q\beta_Q + \varepsilon_Q, \qquad X, W \in \mathbb{E}^{935};\ \beta \in \mathbb{E}^{13}$$

Where:

n = sample size = 935
k = number of independent variables = 12
W = a vector containing n observations of monthly wage, the dependent variable.
β = a vector containing *13* coefficients to be estimated
ε = a classical error term
Q = specified quantile of log(wage). This paper examines the following quantiles: .10 .20 .30 .50 .70 .80 .90

X = an *935*x*13* matrix of the following independent variables (expected sign of the estimated coefficient of the variable is in parenthesis):

Age (+): how old the individual is measured in years.
Black (-): A dummy variable where Black=1 indicates a non-white individual and Black=0 indicates a white individual.
Educ (+): number of the last grade completed (e.g. Education = 8 indicates that the individual has completed the eighth grade).
Exper (+): work experience measured in years.
Expersq: a squared term is added to capture diminishing returns to experience.
Tenure (+): amount of work experience at the present company measured in years.
Tenuresq: a squared term is added to capture diminishing returns to tenure.
South (-): A dummy variable where South=1 indicates residence in the Southern U.S. and South=0 otherwise. The average wage in our sample for a southern resident is about $150 lower than a non-southerner.
Urban (+): A dummy variable where Urban=1 indicates city residence and Urban=0 indicates non-city residence.
IQ (+): the score of the individual on a standardized IQ exam. Scores range from 50 to 145. See bibliography for discussion.
Feduc (+): number of the last grade completed by father (e.g. Education = 8 indicates that the individual has completed the eighth grade).
Meduc (+): number of the last grade completed by mother (e.g. Education = 8 indicates that the individual has completed the eighth grade).

Data

Table 1 below is a brief summary of the data used. The data comes from the young men's cohort from the National Longitudinal Survey. Thus, this individual level data contains only male individuals.

McKinley and Neumark collected the data used in this paper for their 1992 study entitled "Unobserved Ability, Efficiency Wages, and Interindustry Wage Differentials". While they collected data from multiple years, our data set only includes data from the year 1980 and can be found at the following link:

http://fmwww.bc.edu/ec-p/data/wooldridge/wage2

Table 1 - Variable Summary

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	935	957.95	404.36	115	3078
IQ	935	101.28	15.05	50	145
educ	935	13.47	2.20	9	18
exper	935	11.56	4.37	1	23
tenure	935	7.23	5.08	0	22
age	935	33.08	3.11	28	38
black	935	0.13	0.33	0	1
south	935	0.34	0.47	0	1
urban	935	0.72	0.45	0	1
meduc	857	10.68	2.85	0	18
feduc	741	10.22	3.30	0	18
lwage	935	6.78	0.42	4.74	8.03
expersq	935	152.83	105.17	1.00	529.00
tenuresq	935	78.06	88.43	0.00	484.00

We will note a few things. First, there is significant heterskadasticity present in the OLS model with the education variable. This can be shown visually with Graphic 1 and formally with Table 2. The former plots the square of the OLS residuals against education while the latter performs a Breusch-Pagan test. Both lead us to reject the null hypothesis of constant variance.

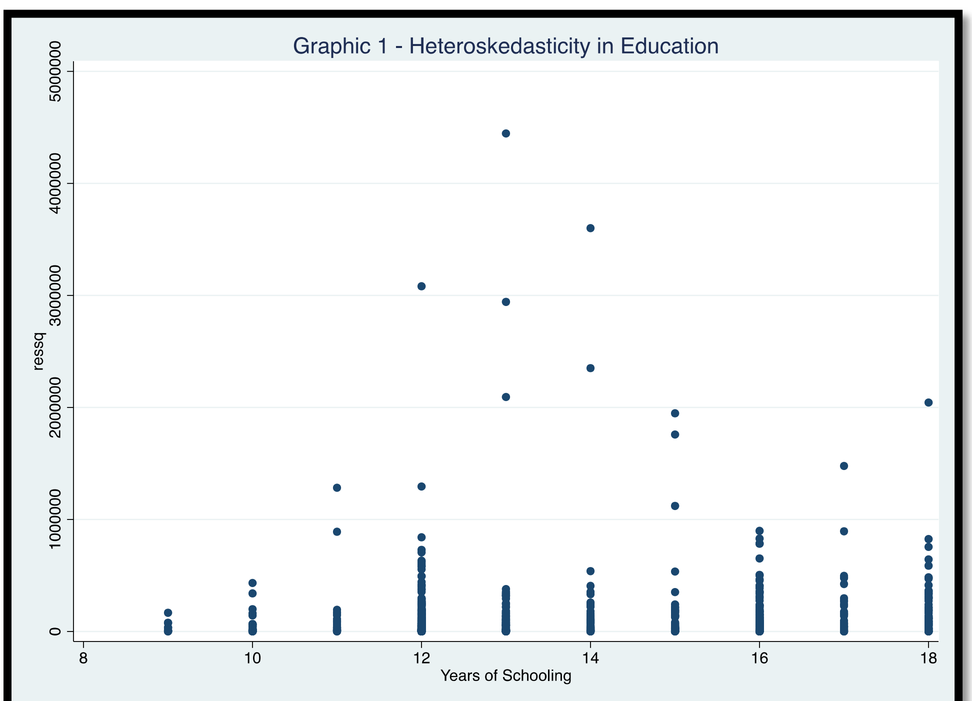
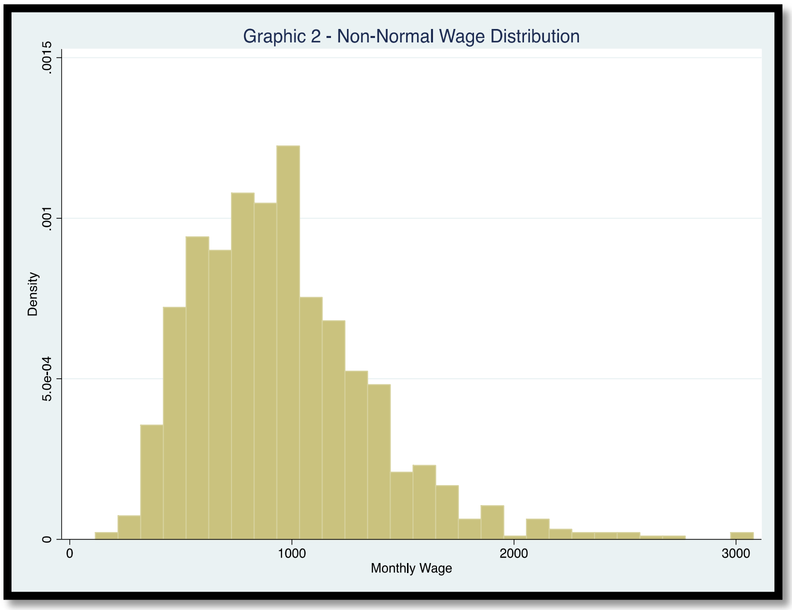
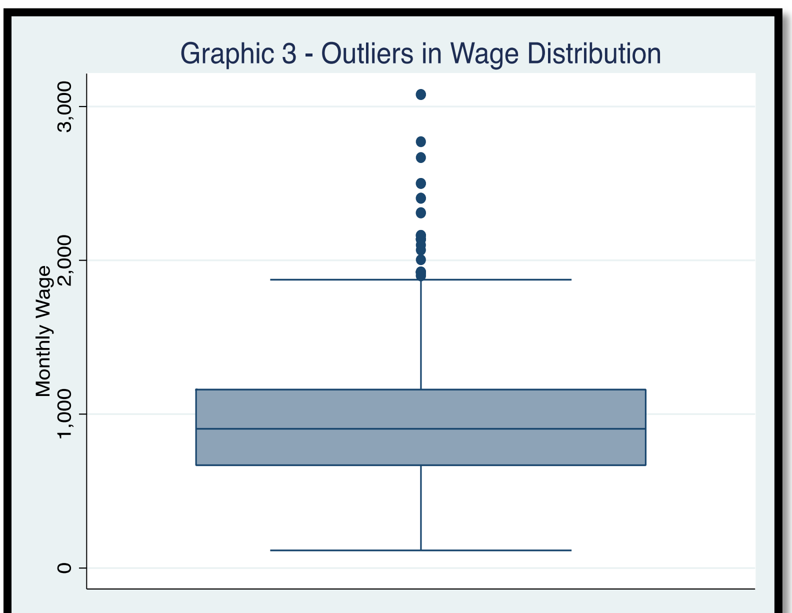


Table 2 - Heteroskadasticity

Breusch-Pagan / Cook-Weisberg Test
Ho: Constant variance
Variables: fitted values of wage
chi2(1) =26.25
Prob > chi2 = 0





A major advantage of quantile regression is that heteroskedasticity is a nonissue because the regression line is not run through the conditional mean of the dependent variable. Rather, it can be run through any specified quantile. By specifying quantiles, our model can investigate the heteroskedasticity, not be harmed by it. Quantile regression is therefore insensitive to outliers in the dependent variable. This is useful because Graphic 2 and 3 clearly show that wage is non-normal and that significant outliers exist.

Furthermore, taking the log of wage does not significantly increase normality. Table 3 provides results for a normality test based on skewness and kurtosis. It reveals that the null hypothesis of normality can be rejected at the 1% level before and *after* taking the log. Graphic 4 shows that outliers still exist after taking the log.

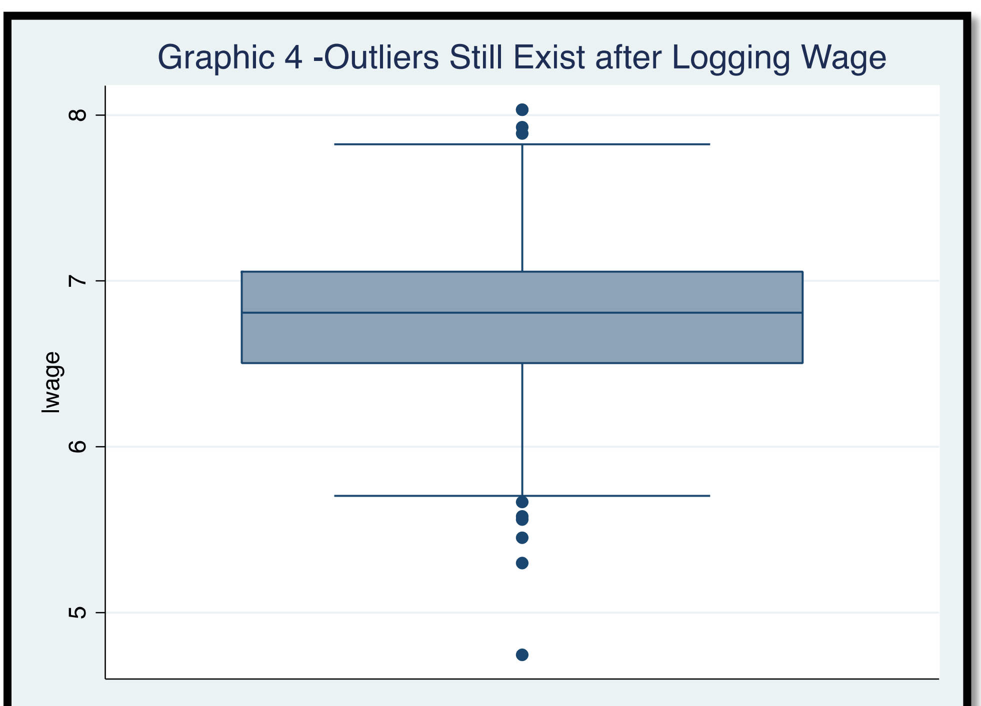
This is precisely where the advantages of quantile regression can be seen. The method handles situations in which the dependent variable's distribution is skewed and has significant outliers, which we have shown to be the case, even after taking the log of the dependent variable.

The reason for the heteroskadasticity in education is intuitive. Those with 12 years of education can only earn so much. They exhibit relatively little variance in earnings. However, after 16 years of education, the variance in earnings increases. After all, both teachers and financers are likely to have 16 years or more of education.

On a similar note, quantile regression is not limited to explaining the conditional mean of the dependent variable. Rather, it allows for the possibility that education can impact earnings differently for different levels of earning. This is exactly the concern of the paper.

Table 3 - Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
wage	935	0	0	.	0
lwage	935	0.0008	0.0064	16.6	0.0002



Results, Discussion, & Shortcomings

In the literature review, it was shown that previous papers analyzing the returns to schooling faced problems with heteroskedasticity and capturing unobserved ability effects. The paper outlined the role of IQ in capturing ability. In the previous section, we outlined the superiority of quantile regression over standard OLS regression in handling dependent variables that exhibit outliers and non-normality. We showed that simply logging the dependent variable is not enough in an OLS regression, but enough for quantile regression.

This section will display and discuss the results of the quantile regression as well as the potential shortcomings of this study.

Table 4 below shows the regression results of a standard OLS regression along with regressions along the specified quantiles. Column 9 contains Wald Tests for each independent variable.

Table 4 - Regression Results

VARIABLES	(1) OLS	(2) q10	(3) q20	(4) q30	(5) q50	(6) q70	(7) q80	(8) q90	(9) Wald Test
IQ	0.00422***	0.00323	0.00409*	0.00393*	0.00546***	0.00483***	0.00476***	0.00388**	0.4
	(0.00116)	(0.00217)	(0.00225)	(0.00211)	(0.00148)	(0.00121)	(0.00126)	(0.00154)	Prob>F =.8798
educ	0.0401***	0.0344	0.0409**	0.0326**	0.0349***	0.0452***	0.0386***	0.0389***	1.18
	(0.00947)	(0.0230)	(0.0191)	(0.0146)	(0.00950)	(0.00950)	(0.00830)	(0.0114)	Prob>F =.3170
exper	0.0134	0.0111	0.0336	0.0164	0.0137	0.0417***	0.0321	0.0222	2.38
	(0.0157)	(0.0275)	(0.0276)	(0.0187)	(0.0176)	(0.0146)	(0.0210)	(0.0234)	Prob>F =.0279
tenure	0.0231***	0.0541***	0.0303**	0.0311***	0.0251*	0.0102	0.0106	-0.00895	1.61
	(0.00876)	(0.0167)	(0.0134)	(0.0104)	(0.0129)	(0.0114)	(0.0100)	(0.0161)	Prob>F =.1424
age	0.0125**	0.0111	0.0114	0.0110**	0.0147*	0.00933	0.0120	0.0104	0.4
	(0.00588)	(0.0153)	(0.00846)	(0.00501)	(0.00787)	(0.00748)	(0.00738)	(0.0111)	Prob>F =.8775
black	-0.103*	-0.0747	-0.123**	-0.145**	-0.0509	-0.0866	-0.0310	-0.0350	1.36
	(0.0526)	(0.0923)	(0.0507)	(0.0576)	(0.0861)	(0.0848)	(0.0938)	(0.0721)	Prob>F =.2293
south	-0.0573*	-0.147*	-0.0909	-0.0970*	-0.0514	0.0104	0.00954	0.0258	2.17
	(0.0329)	(0.0815)	(0.0593)	(0.0519)	(0.0380)	(0.0446)	(0.0323)	(0.0425)	Prob>F =.0442
urban	0.182***	0.155*	0.156***	0.191***	0.229***	0.233***	0.216***	0.143*	0.96
	(0.0306)	(0.0818)	(0.0463)	(0.0419)	(0.0261)	(0.0352)	(0.0514)	(0.0758)	Prob>F =.4517
expersq	-6.01e-06	0.000485	-0.000654	-0.000209	-0.000241	-0.00135**	-0.000961	-0.000390	
	(0.000713)	(0.00131)	(0.00104)	(0.000828)	(0.000746)	(0.000626)	(0.000995)	(0.00108)	
tenuresq	-0.000899*	-0.00220*	-0.000785	0.000980**	-0.000814	-0.000354	-0.000622	0.000282	
	(0.000460)	(0.00129)	(0.000592)	(0.000428)	(0.000596)	(0.000559)	(0.000559)	(0.000875)	
feduc	0.00602	-0.00276	0.00618	0.00567	0.00780	0.00626	0.00537	0.00623	0.34
	(0.00557)	(0.0130)	(0.0112)	(0.00952)	(0.00553)	(0.00679)	(0.00738)	(0.00839)	Prob>F =.9153
meduc	0.00739	0.00479	0.00185	0.00544	0.00895*	0.0104*	0.00964*	0.0179**	0.7
	(0.00591)	(0.0189)	(0.0102)	(0.00829)	(0.00541)	(0.00531)	(0.00558)	(0.00829)	Prob>F =.6534
Constant	4.917***	4.699***	4.571***	4.921***	4.733***	4.904***	5.114***	5.444***	
	(0.224)	(0.409)	(0.416)	(0.232)	(0.277)	(0.279)	(0.245)	(0.280)	
Observations	722	722	722	722	722	722	722	722	
R-squared/Pseudo R-squared	0.244	0.1512	0.1679	0.173	0.1609	0.1485	0.1472	0.1378	

Robust standard errors in parentheses for OLS. Bootstrap SEs are used for quantile regressions (equations 2 through 8). Bootstrap SEs are constructed with 50 replications. Wald Statistics are in column 9.
H0=Equivalent Coefficients Across Quantiles.
*** p<0.01, ** p<0.05, * p<0.1

Firstly, the effect of an additional year of education on monthly wage ranges from 3.4% in the 10th quantile to its peak at 4.5% in the 70th quantile before dropping to 3.9% in the 90th quantile. No serious multicollinearity issues exist, as can be seen in Table 5. The VIFs for experience and tenure are high because of their close relationship with the squared counterparts, as is expected.

Table 5 - Multicollinearity

Variable	VIF
expersq	24.51
exper	21.97
tenuresq	12.59
tenure	12.14
educ	1.88
age	1.74
IQ	1.59
black	1.24
south	1.1
urban	1.03
Mean VIF	7.89

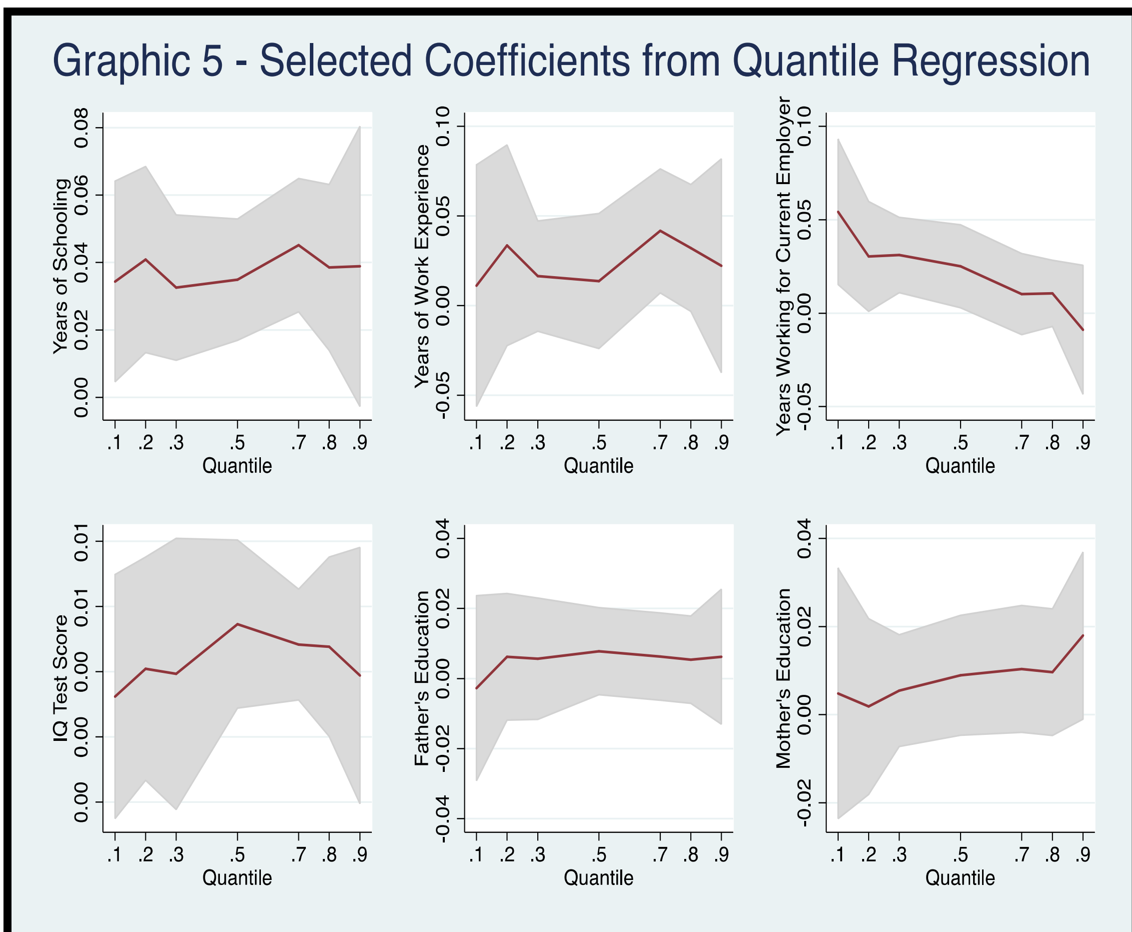
An analysis of the Wald test concludes that we cannot reject the equivalence of the education coefficients across quantiles at the 10%, 5%, or 1% significance levels. This means that the effect of education on earnings is constant from quantile to quantile.

It is worthwhile to compare the regression on the 50th quantile with the OLS regression. The OLS coefficient on educ is 4%. As we would expect, this is much higher than the conditional median (50th quantile regression) of 3.49%. This overestimation of the mean is due to the skewness and outliers present in the lwage distribution. We see that quantile regression does, as predicted, a better job at handling a noisy dependent variable such as lwage. Additionally, an examination of the standard errors indicates that the effect of an additional year of education on monthly wage becomes increasingly more significant going up quantiles as standard errors decline. Furthermore, for earners in the 90th quantile, education is the most statistically significant variable affecting earnings. Comparing this conclusion with quantiles 10, 20, and 30, we see that tenure, not education, is the most significant variable affecting earnings at these lower quantiles.

A quick analysis of feduc and meduc, which control for family effects, is enough to conclude that the father's education level has no significant impact on an individual's earnings. However, for quantiles .5 through .8, the mother's education level is significant at the 10% level. For our highest earnings quantile, meduc is significant at the 5% level. Relative to the other variables, however, the size of its coefficient is small. It makes sense that the mother's education level would be more significant than the father's since mothers tend to bear much of the child-rearing responsibilities in American households. Thus, their educational attainment would have more of an effect on the child's simply because they tend to spend more time with the children.

Interestingly enough, the most impactful independent variable, in terms of coefficient size, is urban. The return to living in a city is 23%, but is only significant in the 70th quantile. IQ is surprisingly significant for several quantiles, but its coefficient is not as large as the coefficient of education. Selected coefficients are graphed in Graphic 5 below.

This model does have some significant shortcomings. For example, in measuring the effect of education, it assumes that sheepskin effects do not exist. An alternative quantile regression accounting for sheepskins can be found in the appendix to this paper. However, there are several problems associates with this model.



Furthermore, IQ could be a faulty measure of ability. If this were indeed the case, then the quantile regressions would be estimating biased coefficients.

The model also ignores the industry effects, which Neumark and Blackburn examine with the same dataset. An employee's industry affects his/her earnings independently of the years of education. A software engineer and high school teacher would both likely have at least 16 years of schooling. However, it is easy to imagine that the engineer would earn a much different monthly wage due to the supply and demand conditions within that particular labor market.

Conclusion

With these problems in mind, this analysis concludes that the return to schooling is about 3.49%, the coefficient on educ from the regression on the 50th quantile of earners. The Wald test concluded that the coefficients are not significantly different from quantile to quantile. So, we choose the conditional median as it is untainted by the outliers and non-normality described in the Data section.

Within the context of the literature review, which described estimates ranging as low as 3% to as high as 15%, 3.49% is on the lower end? Even though it is on the lower end, education is very impactful on monthly wages in our model. In fact, education is a more statistically significant variable for higher earning quantiles. For the 90th quantile, education is the most significant covariate. Other significant variables include IQ and mother's education (meduc). Both were statistically significant for the median quantile onwards.

Going back to the primary motivation for this research (i.e. the decision to attend school), we conclude that the return to education is constant from quantile to quantile. Thus, the decision to take on an extra year of schooling is made by analyzing alternatives to schooling (work experience) and the cost of schooling itself. Let's say that this hypothetical economic actor just graduated college and would like to go into investment banking in order to rise to the top 90th quantile of earners. However, he is considering getting an MBA also. Is this worthwhile? All else equal, simply by comparing the effect of experience and the effect of education, we can say that it makes rational sense for this actor to defer work experience in favor of additional education to earn an MBA. After all, education has a larger and more statistically significant coefficient for this quantile.

Appendix

Table 6 - Sheepskin Regression Results

VARIABLES	(1) q10	(2) q20	(3) q30	(4) q50	(5) q70	(6) q80	(7) q90	(9) VIFs
IQ	0.00233	0.00320**	0.00471**	0.00521***	0.00576***	0.00498***	0.00314*	1.63
	(0.00184)	(0.00141)	(0.00195)	(0.00138)	(0.00111)	(0.00128)	(0.00185)	
educ	0.0394	0.0387*	0.0361*	0.0419**	0.0593***	0.0372	0.0585*	7.48
	(0.0390)	(0.0211)	(0.0188)	(0.0181)	(0.0193)	(0.0232)	(0.0353)	
exper	-0.00462	-0.000707	0.0174	0.0159	0.0429**	0.0304	0.0131	21.18
	(0.0282)	(0.0219)	(0.0134)	(0.0175)	(0.0215)	(0.0237)	(0.0287)	
tenure	0.0356**	0.0351***	0.0312**	0.0242	0.00915	0.0120	0.00356	11.87
	(0.0139)	(0.0131)	(0.0127)	(0.0167)	(0.0101)	(0.0105)	(0.0166)	
age	0.0229**	0.0141*	0.0185**	0.0148**	0.0123*	0.0123*	0.0102	1.86
	(0.00889)	(0.00787)	(0.00810)	(0.00637)	(0.00718)	(0.00691)	(0.00975)	
black	-0.0900	-0.110**	-0.110**	-0.0542	-0.0823*	-0.0376	-0.0692	1.21
	(0.0869)	(0.0547)	(0.0538)	(0.0737)	(0.0447)	(0.0519)	(0.0634)	
south	-0.103	-0.0925*	-0.0690*	-0.0541	0.00837	0.00925	0.0297	1.1
	(0.0661)	(0.0535)	(0.0362)	(0.0406)	(0.0410)	(0.0440)	(0.0550)	
urban	0.134**	0.134***	0.173***	0.226***	0.240***	0.205***	0.177***	1.05
	(0.0561)	(0.0457)	(0.0410)	(0.0310)	(0.0343)	(0.0473)	(0.0534)	
expersq	0.000891	0.000605	-0.000341	-0.000363	-0.00146	-0.000863	9.24e-05	24.04
	(0.00131)	(0.000893)	(0.000561)	(0.000726)	(0.00104)	(0.00109)	(0.00147)	
tenuresq	-0.00108	-0.000907	-0.000916	-0.000729	-0.000273	-0.000721	-0.000388	12.34
	(0.000875)	(0.000780)	(0.000696)	(0.000768)	(0.000499)	(0.000564)	(0.00109)	
hsdegree	-0.0712	-0.0565	-0.0415	-0.0105	0.0301	0.0191	0.0302	1.69
	(0.0639)	(0.0383)	(0.0366)	(0.0274)	(0.0410)	(0.0484)	(0.0828)	
coldegree	0.117	0.0301	-0.0313	-0.0402	-0.0533	0.0179	-0.0642	3.05
	(0.160)	(0.0803)	(0.0614)	(0.0754)	(0.0771)	(0.0923)	(0.165)	
graddegree	-0.157	-0.211	-0.126	-0.0388	-0.0641	0.0105	-0.106	4.15
	(0.222)	(0.156)	(0.125)	(0.111)	(0.0891)	(0.120)	(0.222)	
feduc	0.00619	0.00332	0.00756	0.00678	0.00337	0.00697	0.00292	1.7
	(0.0122)	(0.00969)	(0.00921)	(0.00770)	(0.00629)	(0.00787)	(0.00983)	
meduc	-0.00985	0.00176	0.00395	0.0111	0.0108*	0.00871	0.0195**	1.58
	(0.0155)	(0.00645)	(0.00583)	(0.00735)	(0.00568)	(0.00805)	(0.00807)	
Constant	4.599***	4.859***	4.580***	4.658***	4.550***	5.091***	5.255***	
	(0.509)	(0.330)	(0.240)	(0.301)	(0.263)	(0.309)	(0.474)	
Observations	722	722	722	722	722	722	722	
Pseudo R-Squared	0.1701	0.1813	0.1757	0.1614	0.1499	0.1474	0.1404	

Robust standard errors in parentheses for OLS. Bootstrap SEs are used for quantile regressions (equations 2 through 8). Bootstrap SEs are constructed with 50 replications. Wald Statistics are in column 9. H0=Equivalent Coefficients Across Quantiles.

*** p<0.01, ** p<0.05, * p<0.1

As seen in the alternative model above, adding in the sheepskin dummies does not have much effect on the education coefficient. For some quantiles, it does increase the coefficient to close to 6%. The coefficient is less significant than the previous model. Urban and IQ maintain their significance and effect on monthly wage.

It must be noted that the VIF of education is much higher than 5, indicating that multicollinearity may be inflating the standard errors. Given this inflation, it is unlikely that the coefficient is significant even at the levels indicated. The previous model made much more intuitive and statistical sense. Not only is it unlikely that sheepskin coefficients have negative and insignificant coefficients, it is unlikely that education is so statistically insignificant.

For further discussion on sheepskins can be found in Card's 1992 study and Jaeger's and Park's 1996 study listed in the bibliography.

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