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INDIVIDUAL HETEROGENEITY IN THE RETURNS TO SCHOOLING: INSTRUMENTAL VARIABLES QUANTILE REGRESSION USING TWINS DATA

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ABSTRACT

Considerable effort has been exercised recently in estimating *mean* returns to education while carefully considering biases arising from unmeasured ability and measurement error. We test whether there is individual heterogeneity in returns to education against the alternative that there is a constant return for all workers. To this end we use recent extensions of instrumental variables techniques to quantile regression on a sample of twins to estimate an entire family of returns to education at different quantiles of the conditional distribution of wages while addressing simultaneity and measurement error biases. We find that higher ability individuals (those further to the right in the conditional distribution of wages) do not appear to have higher returns to schooling. We provide evidence of two sources of heterogeneity in returns to schooling. First, there is evidence of a differential effect by which more able individuals become better educated because they face lower marginal costs of schooling. Second, once this endogeneity bias is accounted for, our results provide evidence of the existence of actual heterogeneity in market returns to education arising from a non-trivial interaction between schooling and unobserved individual ability. Our findings have meaningful policy implications.

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1. Introduction

The causal relation between education and earnings has been heavily and carefully explored. The many empirical and theoretical difficulties associated with the analysis of such a relationship have been approached with a remarkable variety of econometric tools on diverse data sets. A well known problem that arises in these studies is that it is difficult to isolate the exact causal impact of additional education on earnings. One must be sure that what is claimed to be the return to additional schooling is not being distorted by the effect of other relevant but unobserved factors that may be related to schooling. More specifically, if unobserved "abilities" in the generation of earnings are related to the level of schooling attained, ignoring such a link would lead to incorrect statements regarding the causal effect of both factors.

In this paper we study the interaction between education and ability explicitly. We take education and ability as two separate factors in the generation of human capital which interact in a non-trivial, unknown way. Most studies estimate the *mean* return to education which may be interpreted as the return to additional schooling for an individual with mean ability. This is a sensible characterization when the return to education is homogeneous across levels of (unobserved) ability. In this work we will be interested in exploring whether people with different ability obtain different returns to education[1]. An homogeneous return that does not vary with ability suggests that any increase in schooling affects earnings in the same way for all individuals in the population, independent of their initial (or given) ability. In this sense, ability and education do not interact in the generation of human capital; both factors have independent contributions to the stock of accumulated human capital. An heterogeneous return to education that varies across individuals with different ability might be an indication that education and ability interact in a non-trivial way. For example, it can be reasonable to think that an individual can compensate for his or her lack of ability by acquiring more education but that he or she can do this only subject to decreasing returns. In this case marginal returns to the accumulation of human capital are decreasing in ability and hence education contributes relatively more to low ability individuals. On the other hand, we might think that ability and education are complements

[1] Card (1995a) concludes by asking, among other questions, "Is the labor force reasonably well described by a *constant* return to education for all workers?"

in the generation of human capital, say, that education has a direct effect on human capital and an indirect effect that comes through the interaction with ability that increases its otherwise constant contribution to earnings. Another way to describe this would be to ask whether education induces a pure location shift, or some more intricate change in the distribution of earnings.

In summary, there are many conjectures that can be made about the interaction between ability and education that, as in the case of any heterogeneous population, are obscured or oversimplified when one concentrates the analysis on the mean return to education

Under these circumstances, the mean return to education is only one summary of a richer pattern of ways that education affects people's earnings according to their ability. In order to explore such an issue, we face several methodological and empirical limitations. First, we do not observe ability, so we cannot model its relationship with education explicitly by including additional regressors based on the former and interaction terms with the later. Therefore, we will consider ability as an unobserved term affecting earnings. Second, education is not randomly assigned to individuals, but it is presumably determined endogenously as function of the level of ability. Technically, we cannot treat education as a predetermined variable, but we should explicitly model the fact that the optimal level of education depends on individual ability. Third, it is well documented (e.g. Griliches,1977, and Ashenfelter and Krueger, 1994) that the schooling variable is typically measured with error, which may introduce serious biases in estimates that do not consider this possibility. Fourth, even though we can make some a priori conjectures about the relationship between ability and education, we do not want to impose unrealistic and unnecessary restrictions on this interaction. We want our empirical model to be exploratory and informative about the nature of this relationship. In the examples mentioned in the previous paragraph the return to education would be a monotonic function of the level of ability, but we see no reason to impose such a restriction.

The interaction between ability and education studied in this work has been directly or indirectly explored in some previous work but, as stressed in Card (1995a), there is little evidence in the empirical literature to support (or reject) the hypothesis of homogeneity in the returns to education. Buchinsky (1994) presents a detailed analysis of the US wage structure using the Current Population Survey (CPS). Although he does not treat the ability-education interaction explicitly, his results based on censored quantile regression methods show that returns to education increase dramatically over the quantiles of the conditional distribution of wages which we may interpret as "ability". Mwabu and Schultz (1996) use quantile methods on a sample of 3117 men for South Africa, and provide some interpretation of their results along the lines explored in our paper. They also obtain varying returns across quantiles. Nevertheless, the results of these studies should be interpreted with caution since they do not handle the problem of measurement errors or endogeneity biases. Heterogeneous returns may be simply reflecting an ability-based endogeneity bias by which more able individuals, facing lower marginal costs of schooling, acquire more education and thus appear to have higher marginal returns to education.

Ashenfelter and Krueger (1994) estimate the mean return to education using multiple measures of schooling on a sample of 298 genetically identical twins. This enables them to handle the measurement error and endogeneity biases using standard panel data methods. However, the parametric framework used in their paper, which concentrates the analysis on the *mean* return, does not take into account the possibility of heterogeneous returns. Ashenfelter and Rouse (1998) analyze an expanded version (three additional years) of the data set used in Ashenfelter and Krueger (1994). They treat the link between ability and education explicitly using a simple parametric representation of this interaction, while also dealing with the endogeneity and the measurement error biases. They find some weak evidence of the existence of a negative relationship between ability and returns to education, suggesting that less able individuals benefit more from additional schooling. However, their approach is fully parametric and therefore imposes rather strong a priori restrictions.

In this paper we use instrumental variables quantile regression methods on the recent sample of 858 genetically identical twins from Ashenfelter and Rouse (1998). Quantile regression methods allow us to estimate returns to schooling for individuals at different quantiles of the conditional distribution of earnings which in this paper we think of as reflecting the distribution of unobservable ability. Unlike traditional regression methods which concentrate on the conditional mean of earnings, quantile techniques allow us to characterize the effect of education on the whole conditional distribution of earnings. We also use testing procedures based on quantile regression statistics to test for the presence of heterogeneity in the returns to education while dealing with endogeneity and measurement error biases. The availability of twins data (with multiple measures of schooling) allows us to use recent extensions of instrumental variables methods to quantile regression to deal with the endogeneity of education arising from measurement error. However, as explained in more detail below, the use of standard panel data methods in a quantile regression context introduces some complications. Instead we control for "family effects" in other ways. Our approach is *semiparametric* in the sense that it imposes a minimal parametric structure on the relationship between earnings and education, without imposing any structure in the key relationship studied in this paper, that is, the relationship between education, ability and earnings.

There are several reasons why economists and policy makers are interested in obtaining accurate measures of the return to schooling. From a "private" point of view, it provides a measure of the premium paid to investment in education. From a social standpoint, the return to education could give an indication of the relative scarcities of people with different levels of education and hence it may provide a guide for educational policies. (See Psacharopoulos and Ng, 1994 for a cost-benefit formulation). If returns to education are not homogeneous across individuals, general policies aimed at increasing the level of education have a more intricate effect on the welfare of the society. On one hand, it is still true that more education contributes positively to poverty alleviation but on the other hand, when returns are heterogeneous, individuals benefit differently from this policy according to their initial level of ability. In this context it is crucial to identify whether the unobservable heterogeneity arises because of actual ability-based differences in the marginal returns to education or because ability-based differences in the implicit marginal costs of schooling induce individuals to acquire different levels of schooling. This distinction turns out to have important policy implications. In particular, the impact of a general educational policy on income distribution needs to be qualified by the presence of these types of heterogeneity. Our goal in explicitly testing for heterogeneity in the returns to education is to help inform the need for formulation of selective educational policies.

The rest of the paper is outlined as follows. In section 2, we specify a simple structural model of schooling choices closely based on Becker (1967), Card (1995a) and Ashenfelter and Rouse (1998). We extend the model by being less restrictive in the parameterization of heterogeneity. In this section, we also provide a brief discussion of quantile regression estimation and testing procedures used in the paper and discuss why quantile regression is so useful in this case. Section 3 briefly describes the data and outlines previous estimates of the mean return to schooling. In section 4, we present the details of model specification and estimation, develop tests for heterogeneity in returns to schooling, and report the results. Section 5 discusses policy implications of our findings and concludes.

2. The Basic Model and its Interpretation in the Quantile Regression Context

In this section we specify a simple structural model that highlights the main aspects of the problem. Following Ashenfelter and Rouse (1998) and Card (1995a) our model is constructed from the Becker (1967) model of investment in education with explicit focus on the following questions: 1) What is a sensible way to think about the link between ability and education? 2). Are returns to education homogeneous across the population? If not, how can we model the source of this heterogeneity and how can it be explored? 3) Why is quantile regression an appropriate tool to explore these types of effects which involve unobservable terms in a non-trivial way? 4) How does the availability of twins data allows us to deal with measurement error and simultaneity bias in the quantile regression framework?

2.1 The Basic Model

The starting point is the utility maximization problem of the i-th twin in family j:

$$\max_{S_{ij}} \quad U\left(Y_{ij}, S_{ij}\right) = \ln\left(Y_{ij}\left(S_{ij}\right) - f\left(S_{ij}\right)\right) \qquad (1)$$

The first term consists of a human capital production function that represents the benefits of acquiring more education $\left(S_{ij}\right)$ and enters the utility function through labor earnings $\left(Y_{ij}\right)$. The second measures the explicit and implicit (opportunity) costs from acquiring more education. As in Card (1995a) and Ashenfelter and Rouse (1998), we specify the benefits term as a linear function in education and the costs to be quadratic:

$$\max_{S_{ij}} \quad U\left(Y_{ij}, S_{ij}\right) = A_j + \alpha F_j + \beta_j S_{ij} + \gamma C_{ij} + e_{ij} S_{ij} - \left(a S_{ij} A_j + \frac{c}{2} S^2{}_{ij} \right) \qquad (2)$$

where A_j represents unobserved family specific characteristics, F_j represents observed family specific variables (age, race), C_{ij} stands for observed individual specific characteristics other than education such as union participation and marital status, e_{ij} is an idiosyncratic error uncorrelated with education, and α, γ, β_j, a, c are the corresponding coefficients. Note that because of A_j and e_{ij} individual preferences for education and earnings differ both within and across families. This can be rewritten more compactly as:

$$\max_{S_{ij}} \quad U\left(Y_{ij}, S_{ij}\right) = b_0\, X_j + b_j Z_{ij} + e_{ij} S_{ij} - \left(a S_{ij} A_j + \frac{c}{2} S^2{}_{ij} \right) \tag{3}$$

with $b_0 = (1, \alpha)$, $b_j = (\gamma, \beta_j)$, $X_j = (A_j, F_j)$ and $Z_{ij} = (C_{ij}, S_{ij})$. We will think of A_j as the ability of individuals that belong to the same family (ie., a pair of twins).

The first order conditions for a maximum are that the marginal benefits *(MB)* of education equal the marginal costs *(MC)* [2]:

$$MB_{ij} \equiv \beta_j + e_{ij} \; = \; MC_{ij} \equiv a\, A_j + c S_{ij} \tag{4}$$

In this simple specification the marginal benefits of education are independent of the level of education and depend on an unobserved family specific component and an idiosyncratic error. As we show below, this leads to standard earnings functions that are log-linear in education[3].

On the other hand, for $c > 0$ the marginal cost is increasing in education. Following Becker (1967), β_j is interpreted as the return to schooling, which in this model is allowed to vary across families. Note that $(a\, A_j)$, which measures the rate at which individuals of the same family substitute schooling for future earnings, also varies to reflect differences in access to funds or tastes for education across families. Since higher ability parents will tend to have higher earnings

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[2] Sufficient conditions for (3) to define a maximum are that $MB_{ij} > 0$, $MC_{ij} > 0$ and $\dfrac{\partial MC_{ij}}{\partial S_{ij}} > 0$, which is equivalent to: $\beta_j + e_{ij} > 0$ and $0 < c > - a\, A_j / S_{ij}$ so that $a < 0$.

and acquire more education, these differences may in turn reflect differences in the wealth or education of the parents across families. For $a < 0$ the marginal cost is decreasing in ability which captures the intuitive notion that more able individuals face lower disutilities of schooling.

From (4) we have that the optimal level of education S^*_{ij} of the i-th twin of family j satisfies:

$$\begin{aligned} S^*_{ij} &= \frac{1}{c}\left(\beta_j - a\,A_j + e_{ij}\right) \\ &= S^*_j + \frac{e_{ij}}{c} \end{aligned} \quad (5)$$

which can be expressed as the sum of a family specific component (S^*_j) and an idiosyncratic error. Note that (5) implies that differences in observed schooling levels in the population arise from two reasons. First, individuals from different families have different returns to schooling (β_j) and different marginal rates of substitution between schooling and future earnings ($a\,A_j$) due to differences in the implicit marginal costs of schooling. Thus, in this model there are two sources of endogeneity bias by which more able individuals also become more educated. Secondly, differences in schooling between twins of the same family are due to optimization idiosyncratic errors that are uncorrelated with the family specific factors that determine optimal education within a family[4]. We assume that:

$$Corr\left(S^*_{ij}, e_{ij}\right) = 0 \quad (6)$$

and that the e_{ij}'s are identically and independently distributed across individuals and families according to an unspecified continuous distribution function G_e. As noted by Ashenfelter and Rouse (1998), (5)-(6) are the fundamental conditions that allow us to identify the returns to schooling from data on earnings and education on a sample of twins.

Integrating MB_{ij} over S_{ij} we obtain the log-linear human capital production function:

[3] See, for example, Heckman and Polachek (1974).
[4] Ashenfelter and Rouse (1998) carried out a variety of tests which provide little evidence inconsistent with this hypothesis.

$$\ln\left(Y_{ij} \right) = \alpha F_j + \gamma C_{ij} + \beta_j S_{ij} + \upsilon_{ij} \tag{7}$$

better known as the Mincer (1974) equation, where $\upsilon_{ij} = \widetilde{e}_{ij} + A_j$ is the unobserved random term of the equation. In the case that attained levels of education were not related to ability, the return-to-education parameter is given by $\partial \ln(Y_{ij})/\partial S_{ij} = \beta_j$, which again is not assumed to be constant across families[5].

As in Ashenfelter and Rouse (1998), consider the case where the heterogeneity in the returns to education takes the following simple linear form:

$$\beta_j = \beta_o + \delta A_j \tag{8}$$

which introduces an explicit link between returns to education and ability. Substituting this in the Mincer equation (7) we get:

$$\ln\left(Y_{ij} \right) = \alpha F_j + \gamma C_{ij} + \left(\beta_o + \delta A_j \right) S_{ij} + \upsilon_{ij} \tag{9}$$

This equation [together with (5)] determine the joint distribution of earnings and education. These equations make it clear that in our model unobserved ability induces two types of heterogeneity in this joint distribution. First, more able individuals tend to have higher absolute earnings (a higher intercept in (9)) and face lower marginal costs of schooling so that they also become better educated. This implies that estimates of the returns to education obtained from equation (9) are affected by a potential endogeneity bias. Second, as long as $\delta \neq 0$ so that there is an interaction between ability and education, the marginal return to education varies with ability. In regards to Card (1995a)'s question (see footnote 1) this implies that the labor market cannot be well characterized by a single rate of return to education[6].

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[5] Note that in these exercises of comparative statics one is interested in the impact of the acquisition of one additional year of education on earnings of an individual randomly selected from the population.

[6] Note that this also contributes to the endogeneity bias by which higher ability individuals tend to acquire more education.

Our model can be used to illustrate the underlying structural relationships that give rise to the two types of heterogeneity mentioned above. Thus, substituting in (8) into (4), at the optimal level of schooling S_{ij}^{*} we have that:

$$\frac{\partial \ln(Y_{ij})}{\partial S_{ij}\, \partial A_j} = \frac{\partial MB_{ij}}{\partial A_j} = \delta \tag{10}$$

Then, δ captures how ability affects the return to one more year of education. As long as $\delta \neq 0$ the return to education will not be constant across individuals with different abilities so that there exists a family of returns to education. If $\delta > 0$ ability enhances the productivity gains of acquiring an additional year of education, while if $\delta < 0$ high ability individuals face lower returns to investment in education[7].

Similarly, from substituting (8) into (2) we have that:

$$\frac{\partial^2 U_{ij}}{\partial A_j\, \partial S_{ij}} = \delta - a \tag{11}$$

which measures the rate at which an individual can substitute ability and education in the generation of utility. When $\delta < a$ the marginal rate of substitution between ability and education is decreasing with the level of ability: the same amount of schooling substitutes less ability as an individual becomes gradually better educated. A similar interpretation holds if the inequality is reversed. In essence, the schooling decision of an individual in the j-th family depends at the margin on the balance of the marginal benefits and costs from additional schooling given his or her endowment of ability A_j. Since $a < 0$ is assumed for an interior solution, in the case that $\delta > 0$ we have that both effects work in the direction of enhancing the ability-based endogeneity bias.

[7] Note that the standard specification and estimation of the Mincer equation (9) with OLS and assuming $\delta = 0$ implicity implies that education and ability are "perfect substitutes" in the production of human capital.

Note also that in practice the well-known problem of measurement error in observable education levels in regards to true schooling levels adds additional problems of endogeneity to any attempts of estimating the Mincer equation (9) consistently. It is then clear that any successful estimation strategy aimed at fully characterizing the conditional distribution of earnings given observed education levels ought to address both the simultaneity (endogenous schooling) and heterogeneity (varying return to education) ability biases as well as the measurement error in education.

First, let us consider the endogeneity bias induced by a failure to control for unobserved family specific ability. Clearly, even when β_j is constant ($\delta = 0$) the OLS estimator of this coefficient performed directly on the observable factors of (9) yields inconsistent estimates since the optimal level of S_{ij} depends on A_j. This is precisely the source of the ability bias extensively discussed in the returns to education literature. Only in the special case that $\delta = a$ would OLS on (9) yield an unbiased (though imprecise) estimate of the return to education. In this case, any lack of ability can be compensated with more education at a constant rate, independent of the ability of the individual. Since in general $E\left(\nu_{ij} \mid S_{ij}\right) \neq 0$, because of (5), OLS estimates of the Mincer equation are biased and inconsistent.

In the previous literature on estimation of the returns to education using twins data this problem was addressed in two ways. One approach is to treat A_j as an unobserved random family effect and focus the interest on obtaining unbiased estimates of the structural coefficients β_j measuring the returns to education. This can be accomplished by directly estimating a "fixed effects model" based on the following (within) differenced equation for each pair of twins:

$$\ln\left(Y_{1j}\right) - \ln\left(Y_{2j}\right) = \gamma\left(C_{1j} - C_{2j}\right) + \left(\beta_o + \delta A_j\right)\left(S_{1j} - S_{2j}\right) + \xi_j \qquad (12)$$

where $\xi_j = \widetilde{e}_{1j} - \widetilde{e}_{2j}$. Note that, given (5)-(6), $E\left(\xi_j \mid \Delta S_{ij}\right) = 0$ where Δ is the difference operator, so that OLS on differenced data yields consistent estimates of the return to education. This is the strategy adopted by Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998) to deal with the ability bias in the OLS context.

An alternative approach is to try to parametrize and estimate the endogeneity (omitted variable) bias explicitly including some proxy for unobserved ability as an additional regressor in equation (9). As long as the proxy can account for most of the endogeneity bias, this approach also allows one to obtain unbiased estimates of the returns to education. Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998) also provide such estimates of the returns to education and the resulting endogeneity bias.

Second, the availability of twins data provide an interesting way to address the problem arising from the measurement error in schooling levels. Each twin is asked to report on the education level of his or her sibling. These cross-reports of each sibling's education can then be employed using standard instrumental variables methods as reported in Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998).

Finally, note that even in the absence of an endogeneity ability bias, we have that $\partial \Delta \ln\left(Y_{ij}\right) / \partial \Delta S_{ij} = \beta_o + \delta A_j$ is not constant and varies with ability, as discussed above. In the former equation, a negative δ means that returns to education are lower for high ability individuals, which in our structural model is interpreted as a decreasing marginal rate of substitution between ability and education. In this case low ability individuals benefit more from additional education. An analogous interpretation holds for positive δ. Note that OLS on (12) only gives a measure of $\partial E\left(\Delta \ln\left(Y_{ij}\right) \mid \left(\Delta S_{ij}, \Delta C_{ij}\right)\right) / \partial \Delta S_{ij} = \beta_o + \delta \overline{A}$: the return to education for an individual with *mean* ability as pointed out by Card (1995a), and therefore masks the variability that may arise if there is an interaction between education and ability.

Since the mean does not provide a complete summary of an inherently heterogeneous population, this calls for an estimation strategy that provides a more complete characterization of the whole family of returns to education in different parts of the conditional distribution of wages. This is precisely the core question that this paper tries to address and is discussed in some detail in section 2.3. First, we briefly discuss the econometric techniques used in the paper to address this question.

2.2 The Econometrics of Quantile Regression

2.2.1 Regression Quantiles

In this section we present some basic results on the quantile regression methods that will be used in this work. This exposition is largely based on Sosa-Escudero (1997). See Koenker and Portnoy (1997) for a recent comprehensive overview of the topic. The problem of estimating a relationship between a random variable Y and a set of explanatory variables X is traditionally reduced in econometric practice to formulating a model for the mean of Y conditional on X, and a particular functional form is specified for this (mean) regression equation. In particular, it is typical to consider the following linear model:

$$Y = X\beta + u \tag{13}$$

where u is a vector of independent error terms whose *i-th* component has an unspecified distribution function F_i. Given the usual conditional orthogonality assumption on the error term, Ordinary Least Squares regression provides a model for the conditional mean of Y given by:

$$E\left[Y / X\right] = X\beta \tag{14}$$

In the special case of *iid* errors this Least Squares estimate of the conditional mean function together with some measure of dispersion would usually provide a complete characterization of (13). If additionally, F_i is assumed to be Gaussian, then OLS regression yields the optimal estimator of location for the linear model (13).

Nevertheless, recently econometricians are increasingly recognizing that the *iid* linear model is not well suited to analyze some real world problems which very often involve heterogeneous populations. In this case if the purpose of the modeling problem is to provide a complete characterization of the conditional distribution of Y on X one needs to think of summary measures other than the mean. In general, one could formulate the following model for the τ-th conditional quantile of Y:

$$Q_\tau = X\,\beta(\tau) \qquad (15)$$

where the orthogonality condition on u is now assumed for $Q_\tau(u|X)$, that is, the τ-th conditional quantile of the error term is assumed to be zero. This gives rise to a *family* of (quantile) regression curves, one for each τ, which provide a more complete characterization of the relationship between Y and X compared to the one given by the mean regression, which concentrates on the first conditional moment. Estimation of the $\beta(\tau)$ coefficients (called "regression quantiles") is based on a sample of n observations of Y and p explanatory variables collected in the matrix X. It can be shown that estimates of β(τ) can be obtained as solutions to the following linear programming problem (see Koenker and D'Orey (1987)):

$$\min_{(\beta,\, u,\, v) \in R^p x\, R_+^{2n}} \left[\ \tau 1'_n\, u + (1-\tau)\, 1'_n\, v \ \ |\, X\beta + u - v = Y \right] \qquad (16)$$

where $1'_n$ is an n vector of ones and u and v are the positive and negative parts of the residual vector.

In addition to providing a more complete representation of the relationship of interest, quantile regression offers the usual robustness properties associated with ordinary sample quantiles since the quantile regression estimator is robust to outlying observations in Y. Note that in the case of the *iid* linear model the conditional quantile functions given in (15) will be parallel vertical displacements of one another. In this case only robustness arguments would lead one to prefer alternative estimators of location other than OLS.

An interesting case arises when the estimated β(τ) coefficients differ systematically across τ's, suggesting that the marginal effect of a particular explanatory variable is not homogeneous across different quantiles of the conditional distribution of Y. This *quantile regression* model introduced by Koenker and Bassett (1978) provides a semiparametric alternative to least squares that handles heterogeneously distributed unobservables in an informative and constructive fashion

Inference on the $\beta(\tau)$'s can be based on the following result. Let $b_n = (b_n(\tau_1), \ldots b_n(\tau_m))$ be a *pm* vector of *p* estimated regression quantile coefficients for *m* different quantiles based on a sample of *n iid* observations; and let β be its population counterpart. Under some regularity conditions Koenker and Basset (1978) showed that:

$$\sqrt{n}\,(b_n - \beta) \;\rightarrow\; N(0, \Omega \otimes Q_0^{-1}) \tag{17}$$

where Ω is a m x m matrix with typical element:

$$\omega_{ij} = (\min(\tau_i, \tau_j) - \tau_i \tau_j) \;/\; [\, f(F^{-1}(\tau_i))\, f(F^{-1}(\tau_j))\,] \tag{18}$$

Q_0 = *plim* n^{-1} $(X'X)$, a positive definite matrix, and $\otimes$ denotes the Kronecker product. Confidence intervals can be easily constructed based on this result. General linear hypothesis like H_0: $H\beta=h$ can be tested using the following Wald-type statistic:

$$T_n = (H\, b_n - h)'\,[\, H\, (\Omega \otimes (X'X)^{-1})\, H'\,]^{-1}\, (H\, b_n - h) \tag{19}$$

which under the null hypothesis has a χ^2 distribution with *rank(H)* degrees of freedom. This approach requires the estimation of the nuissance parameter $1 / f(F^{-1}(\tau))$ (called *sparsity*) which measures the inverse of the density of the observations around the τ-th quantile. This is usually accomplished based on estimates of the empirical quantile function constructed from residuals of the τ-th quantile regression and using smoothing techniques. See Koenker (1994) for a discussion of the alternative procedures for estimating the sparsity[8].

In particular, we will be interested in testing whether the slope parameters of different conditional quantile functions are significantly different. A simple test based on (19) proceeds by testing whether pairs of slope coefficients are equal at two different quantiles. Suppose we want to test whether the *k*-th slope coefficient is equal at two different quantiles. This corresponds to estimating the model for *m*=2 quantiles and computing the statistic (19) setting *h*=0 and *H* equal to a (1 x 2p) matrix with one in the *k*-th position, minus one in the (*k*+*p*)-th position and zero

[8] In this paper we have used the approach suggested by Basset and Koenker (1982) to estimate the sparsity and the Hall and Sheather (1988) bandwidth rule. These are discussed in Koenker (1994).

elsewhere. Koenker and Bassett (1982) show that such a test is essentially a test for heteroscedasticity where, under the alternative hypothesis, the conditional variance of u is a linear function of the k-th explanatory variable. The test is robust in the sense that no parametric assumptions are made on the distribution of the error term of the model. This is the test procedure we use in the paper to test formally for the presence of heterogeneity in the returns to education.

An alternative approach to inference that takes advantage of the quantile regression formulation can be based on *rank* tests. These tests are robust to outliers in Y and are asymptotically distribution free since they do not require the estimation of nuissance parameters depending on the error distribution. They are not more complicated to compute than those based on estimation of the sparsity. The theory of tests of linear hypotheses based on ranks has been established by Guttenbrunner, Jureckova, Koenker and Portnoy (1993, GJKP hereafter) and since we do not attempt to summarize the theory of such tests here we refer to GJKP and Koenker (1994) for a review. Let $X=[1:X_1:X_2]$ and suppose we are interested in testing the linear hypothesis H_0: $\beta_2 = 0$ vs H_0: $\beta_2 \neq 0$. The following statistic proposed by GJKP (1993):

$$W = (Y_r'M X_2 (X_2'M X_2)^{-1} X_2'M Y_r) / A \tag{20}$$

where Y_r is an estimated vector of ranks of the observations, $M = I - X_1\left(X_1' X_1\right)^{-1} X_1'$ and A is a quantity that does not depend on the distribution of the errors. Visual inspection suggests that the rank-based test is very similar to Lagrange multiplier tests where the y_i's play the role of the square residuals. This statistic has an asymptotic χ^2 (q) distribution under the null hypothesis. The key ingredient in this procedure is the estimation of the ranks vector, which can be obtained as a by-product of the computation of the regression quantiles for the linear model under the restricted model. Based on the well known duality between hypothesis testing and construction of confidence intervals, a test to evaluate the significance of a single variable can be inverted to obtain a confidence interval for each coefficient. Koenker (1994) discusses in detail computational and theoretical advantages as well as montecarlo results in favor of these tests. In this paper we used this approach to construct confidence intervals for the vector of quantile regression coefficients obtained in the Non-IV models.

2.2.2 Instrumental Variables Quantile Regression

As in the OLS case, when some of the explanatory variables are determined simultaneously with the response variable, a bias arises due to the existing dependence between the regressors and the error term. Following Powell (1983), the data might be viewed as being generated by the following structural equation:

$$Y = Y_1 \gamma + X_1 \beta + u \tag{21}$$

Using the terminology familiar from the simultaneous equations literature, Y is the response variable, Y_1 is a n x g matrix of endogenous variables determined simultaneously with Y, γ is the vector of associated coefficients and X_1 is a n x k_1 matrix of exogenous (predetermined) regressors. The simultaneity of Y and Y_1 induces a bias in both OLS and RQ estimators. Assuming that there is a set of k_2 instrumental variables collected in the matrix X_2, this estimator can be given a two-stage interpretation analogous to Theil's classical interpretation of the Two-Stages Least Squares estimator. In the first stage we project the explanatory variables on the space spanned by the instruments which are, by assumption, uncorrelated with the error term. The second stage performs quantile regression of the response variable on the projections obtained in the previous stage. Thus, the Two-Stage Quantile Regression Estimator is defined as any vector ξ_τ that solves (19) for the model specified in (21) where Y_1 is replaced by its first stage OLS projection on the matrix of exogenous variables (including the instruments).

The large-sample properties of this estimator were established by Chen (1988) extending Corollary 3.1 in Powell (1983). Consider the following models:

$$Y = X \Pi_1 + V \tag{22}$$

and

$$Y_1 = X \Pi + v \tag{23}$$

where $X = [X_1, X_2]$ is a n x $(k_1 + k_2)$ matrix collecting all the exogenous variables. Equations (22)-(23) are, respectively, reduced forms of the variables Y_1 and Y, while V and v are vectors of i.i.d. error terms.

Under some regularity conditions, the asymptotic distribution of the two-stage regression quantile estimator, based on Chen (1988) and Corollary 3.1 of Powell (1983), is given by the following result:

$$\sqrt{n}\,(\xi^*_\tau - \xi_\tau) \;\rightarrow N(0, C\,Q^{-1}) \tag{24}$$

$$C = E\,[f(F^{-1}(\tau))^{-1}\;\varphi_\tau(v_i) - V_i\,\gamma\,]^{-1} \tag{25}$$

where $Q = plim\; n^{-1}(Z'Z)$ with $Z = (X\,\Pi_1\,,\,X_1)$, $\varphi_\tau(v_i) = \tau - I(v_i < 0)$ is the τ-quantile score function, F and f are the distribution and density functions of v_i, the residuals from the first stage projection of Y on the matrix of exogenous variables.

In practice Q is estimated by $n^{-1}(Z^{*\prime}Z)$ with $Z^* = (X\,\Pi^*_1\,,\,X_1)$ and Π^*_1 is the OLS estimate of Π_1 in equation (22), v_i and V_i are replaced by the residuals of the least squares fit of equations (22) and (23) respectively, with $u_i = v_i - V_i\,\gamma$, and γ is replaced by its (consistent) quantile regression estimate obtained from equation (21) in the second stage of the estimation process. The expectation term is estimated by its sample analogue. This also requires the estimation of the sparsity function which is carried out using non-parametric smoothing techniques[9].

2.3 Interpretation of the Model in the Context of Quantile Regression

Ashenfelter and Rouse (1998) address the question of heterogeneous returns to schooling by directly estimating the correlation between ability and schooling using the average education of a pair of twins from family *j* as a proxy for ability in that family. The drawback of this approach is that the resulting estimate of the heterogeneity parameter relies on a full parametrization of unobserved ability. We want to be able to characterize the family of returns to education without making such parametric assumptions about unobservable ability A_j.

[9] The Hall and Sheather (1988) bandwidth rule is again used in this case.

As mentioned earlier the regression quantiles of Koenker and Basset (1978) provide a more general way to explore and estimate heterogeneity in the returns to schooling. Buchinsky (1994) comes close to such a characterization by estimating quantile wage equations using CPS data. Indeed, he finds that the returns to education increase across quantiles of the conditional wage distribution providing evidence of the existence of heterogeneity in the returns to education. Mwabu and Schultz (1996) also used quantile regression on household survey data on wages for South African men to estimate the returns to education and also found evidence against the hypothesis of a single rate of return.

Nevertheless, none of this work addressed the problem of endogeneity bias nor does it structurally model the source of heterogeneity. Since (5) implies that $Q_\tau(v_{ij} \mid S_{ij}) \neq 0$ (as long as $\delta \neq a$), quantile regression on a Mincer equation like (9) would yield inconsistent estimates of the family of returns to education. In fact, if the endogeneity bias varies across quantiles of the conditional distribution of wages, as is likely to be the case, the varying returns to education obtained from quantile wage regressions that do not control for unobservable ability (as in the above work) may just reflect differential endogeneity biases across quantiles rather than actual ability-based differences in the market marginal returns to education. Therefore, one would cast doubt on the heterogeneity estimates from the above mentioned quantile wage regressions.

Our goal in this paper is to find whether there is evidence for "true" heterogeneity in the returns to education while addressing both the simultaneity (endogenous schooling) and measurement error biases.

A naïve way around this problem is to consider quantile regression on a differenced Mincer equation like (12), in which case since $Q_\tau(\Delta\xi_{ij} \mid \Delta S_{ij}) = 0$. Therefore,

$$\frac{\partial\, Q_\tau\left(\Delta \ln\left(Y_{ij}\right)\right)}{\partial \Delta S_{ij}} = \beta_o + \delta\, Q_\tau\left(A_j\right) = \beta_o + \delta\, G_A^{-1}\left(\tau_j\right) \qquad (26)$$

where G_A is the distribution function of abilities in the population. This seems to suggest that one could obtain consistent estimates of the whole family of returns to education along the distribution of abilities. This approach would not allow us to identify δ directly, but its sign can be easily recovered by observing that:

$$\beta(\tau_k) - \beta(\tau_j) = \delta \left(Q(A;\tau_k) - Q(A;\tau_j) \right) \tag{27}$$

and that $Q(A;\tau_i)$ is monotonic for $\tau_j < \tau_k$. Then, the interaction between education and ability could be explored by comparing $\beta(\tau)$'s at different quantiles τ_k and τ_j, for $i \neq j$. This also suggests that a simple test of the hypothesis of heterogeneity ($\delta = 0$) can be based on a test of whether the estimated coefficients for the returns to education differ across quantiles, using the test for heteroscedasticity proposed by Koenker and Bassett (1982).

Note that unlike Ashenfelter and Rouse (1998) this approach does not require one to impose parametric restrictions on the type of interaction between ability and education. In fact the approach remains valid even for specifications of heterogeneity in the population more general than the one we consider in (8)[10].

Nevertheless, there is a fundamental drawback with the previous approach. Regression quantiles estimators are not obtained directly from the type of vectorial projections involved in OLS, instead these estimators exploit the sign of regression residuals. (Honore and Powell, 1984). Since by the convolution theorem quantiles of the sum of two random variables are not equal to the sum of the quantiles of each random variable at a given τ_j, it is not possible to recover the estimates obtained using data on levels on an equation like (9) from the estimates of quantile regressions on an equation like (12) based on differenced data. In effect, the results one would get by using a "differenced" specification in the quantile regression framework would be erroneous. Although differencing in the least squares context can be shown to be equivalent to a fixed effects estimator, in the context of quantile regression, this is not the case. In fact, when differencing in quantile regression, the *order* of the individuals matters[11]. As a result, in the

[10] As discussed in Koenker and Bassett (1982), the linear scale heteroscedastic model considered here encompasses many of the models of heteroscedasticity considered in the econometrics literature.

[11] The natural attempt to estimate the fixed effects model including family specific dummies is also futile in this case given the unavoidable ambiguity surrounding the identification of the fixed effects at any given quantile with only two observations per family.

final empirical section of the paper, we do not "difference" the data but try to control for the family fixed effect by using the education level of the father of the twins as an additional regressor[12]. We also experimented with other regressors as proxies for the family "fixed effect" and discuss robustness across these measures below.

3. Data Description and Previous "Mean" Results

The data used in this paper were collected over a span of five years at four meetings (August of 1991, 1992, 1993, and 1995) of the Annual Twins Festival in Twinsburg Ohio. Many of the questions are similar to questions asked in the CPS with some twins-specific questions added. As Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1997) show the mean characteristics of the sample are quite similar to the population at large. Sample characteristics are reported in table 1. The sample we use has, on average, more years of education, higher income, and is more likely to be female and white than the population at large.

Table 2 reports regression results employing econometric specifications similar to Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998) and Rouse (1997) which focus on estimating the *mean* return to education. We briefly present these results for three reasons. First to highlight (as in the previous literature) the importance of considering both ability and measurement error biases in estimating mean returns to education. Secondly to document the mean return to education using these specific data. Finally, Table 2 provides a summary of the data and specifications that will be extended to the quantile regression framework below.

The first five columns of Table 2 estimate models in levels and the second four do so in differences. Column 1 of Table 2, reports the simple least squares regression of the log of earnings on age, $(age)^2$ a gender indicator and an indicator equal to 1 if the respondent is white. This model is estimated using all 858 respondents for which we have complete data. In column 2 we have included additional controls for marital status, union coverage and tenure. As usual, there is a positive seniority profile, and the female indicator is large and negative. The white indicator is also negative (as in Ashenfelter and Krueger, 1994, Ashenfelter and Rouse, 1998,

[12] Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998), and Rouse (1997) also present some estimates using the average schooling level of the twins as a proxy for family

and Rouse, 1997). The return to education estimated in column (1) is $e^{0.108}-1 \cong 11.4$ percent. As we have stated earlier and as is well documented in Griliches (1977) and Ashenfelter and Krueger (1994), this estimate is potentially upward biased due to unobserved ability and downward biased due to measurement error. Ashenfelter and Krueger (1994) found that, when controlling for measurement error and ability bias, the mean return to education is as high as 12 - 16 percent – much higher than the conventional least squares estimates. Card (1995a) provides a useful summary of six other papers that also find that least squares estimates seem to be downward biased[13].

The other columns in table 2 present the results of estimating additional, yet similar, specifications that address these ability and measurement error biases. Column 8 of table 2 is our estimate that is most closely related to Ashenfelter and Krueger's (1994) final estimate (re-printed in our Table 2, column 9). This is the differenced model using instrumental variables where the instrument is the first twin's report of the second twin's education minus the second twin's report of the first's. Our resulting estimate 0.119 is not unlike the least squares estimate of 0.108 but is lower than Ashenfelter and Krueger's (1994) similarly specified estimate of 0.167. Rouse (1997) using the same four years of data that we use[14] (Ashenfelter and Krueger, 1994 use only one year) estimates and points out that "Unlike the results in Ashenfelter and Krueger, I find that the within-twin regression estimate of the effect of schooling on the log wage is *smaller* than the cross-sectional estimate, implying a small upward bias in the cross-sectional estimate." She further notes, however, that her results and those of Ashenfelter and Krueger are not statistically different and that the difference is perhaps due to sampling error. In the next section we draw attention away from estimating the mean return toward estimating and testing for heterogeneity in returns to schooling.

4. Estimation Details and Empirical Results

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ability.

[13] These studies are Angrist and Newey (1991), Angrist and Krueger (1991), Angrist and Krueger (1992), Butcher and Case (1994), Card (1995b), and Kane and Rouse (1995). Card (1995a) also points out that "In his widely cited 1977 survey, Griliches concluded that ordinary least squares (OLS) estimates tend to give unbiased or even negatively biased estimates of the causal effect of education. It is interesting to speculate as to why the conventional wisdom is at odds with Griliches's carefully argued conclusion."

[14] See Rouse (1997) table 4.

This section outlines in more detail the framework we use in the empirical part of the paper. This is vital to the development of the empirical models of the paper as it provides us with the tools to develop formal tests for heterogeneity in returns to education under the presence of endogeneity and measurement error biases. In Sections 4.1 to 4.6 we detail the specifications we use broadly, describe the estimation and the strategies for testing equality in the returns to schooling across various quantiles, and discuss the empirical results.

The focus of this paper is on estimating and testing for heterogeneity in returns to schooling across quantiles of the conditional wage distribution while addressing endogeneity and measurement error biases. To this end, we will consider four empirical models: 1) the levels model without instrumental variables, 2) the levels model with instrumental variables, 3) the family effects model without instrumental variables, and 4) family effects model with instrumental variables. The ideas behind these models roughly follow the empirical work in the recent literature on twins (Ashenfelter and Krueger, 1994, Ashenfelter and Rouse, 1998, and Rouse, 1997) replicated in Table 2. Since the levels model without instrumental variables is the simplest case, we begin there.

4.1 Levels Model Without Instrumental Variables

Figure 1 presents the quantile regression estimates of the returns to education for the levels model without instrumental variables. The figure is separated into five sub-figures according to the covariates included in the estimation: in addition to controlling for education these control for A) education only, B) age, race, and gender only, C) ("all" but tenure) controls for age, race, gender, married, and union, D) ("all" but union) controls for age, race, gender, married, and tenure, and E) controls for age, race, marital status, union, and tenure. This, final case, which we call "all," includes the broadest set of covariates, and receives particular attention in this paper.

The $\beta(\tau)$'s for 0.05 to 0.95 in increments of 0.05 are plotted in Figure 1 for the levels models without instruments. We focus our attention on the specification that includes all covariates (Figure 1E). The actual returns for each of the 19 quantiles from 0.05 to 0.95 are also reported in Table 3A, panel A with 95% confidence bounds for the specification including all covariates. A cursory examination of the figures suggests the presence of heterogeneity in the returns to education. The returns are, in general, increasing for higher quantiles of the conditional distribution of wages. In particular, the median return to education from Table 3A, panel A is 0.113 (compared to the mean return of 0.120 reported in column 2 of Table 2). However there is a striking increase in the return from the low quantiles to the high quantiles going from 3.6% at the 0.05 quantile to 11.0% at the 0.95 quantile. Note also that the magnitude and the pattern of the estimates of the returns to education remain remarkably similar across specifications.

We test whether the observed differences are statistically significant across quantiles and report the results of such tests in Table 3B, panel A. Several of the tests of equality of returns between various quantiles reject the hypothesis of homogeneous returns at a 1% significance level. For example, there is a statistically significant difference between the returns at the 0.25 and 0.50 quantiles (t-statistic = 10.5326, p-value = 0.0012). This suggests that, in general, the returns are significantly different across several quantiles. These findings are consistent with the existence of a complementary relationship between ability and education in the generation of earnings[15]. Note, however, that comparisons at higher quantiles are not significantly different. Another way to see this is that Figure 1 flattens out in the right tail.

4.2 Levels Model with Instrumental Variables

Of course, our first empirical specification is subject to the two main criticisms described by and controlled for in Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998) for the mean return to education. We take the first step toward addressing these problems by estimating the levels model using instrumental variables for the education variable to alleviate the measurement error problem. Although there are several options for instruments for own reported education we follow the previous literature and use the sibling's report of one's own education. These results are reported in Figure 2 which is arranged like Figure 1 in that we report results for five different sets of covariates. Again, we have reported the returns to education for the 19 quantiles 0.05 to 0.95 in Table 3A panel B with 95% confidence bands for the specification including all covariates.

[15] Note nevertheless that the tests do not support the hypothesis of strict monotonicity in the pattern of estimated returns.

The same general conclusions drawn from Figure 1 may be drawn from this figure. In particular, after controlling for measurement error in the levels model, we see evidence of heterogeneity in returns to education with increasing returns at higher quantiles. The results suggest that failure to address the measurement error in education in the levels model doesn not seem to create a significant downward bias in the estimated returns to schooling. Notice, however, that the standard error bands are somewhat wider in the instrumental variables case so even if there are small differences, they are unlikely to be significant[16]. Clearly this will also have an effect when we do testing for homogeneity of returns across quantiles.

We report tests of significance in the levels model with instrumental variables in Table 3B, panel B. Here the results are largely consistent with those in the levels model without instruments. Overall, these findings suggest that the bias that arises from measurement error in education is not very important. In the absence of an endogeneity ability bias, the estimates from the previous levels models would provide relatively accurate measures of the family of conditional quantile functions of the wage distribution.

4.3 Family Effects Model Without Instrumental Variables

This section and the one that follows repeats the analysis of sections 4.1 and 4.2 with the additional innovation that we attempt to control for the well-known ability bias problem (Griliches, 1977). As discussed earlier, in the context of estimating the mean return to education this has been done by including a family fixed effect in the regression or by differencing the data. As we stated in section 2.3 above, the quantile regression analogue of estimating an OLS fixed effect or differenced model is a non-trivial exercise. Instead, in our quantile regression equivalent of a fixed effects model we use the father's level of education as a proxy for the family effect. Essentially we are re-doing the analysis reported in Figures 1 and 2 and Tables 3A and 3B with the additional covariate which is the father's schooling level[17]. Note that even

[16] These larger standard errors are in part due to the fact that the estimation of the variance-covariance matrix for the instrumental variable estimator relies on estimation of the sparsity function which is not estimated with much precision in the tails of the distribution of wage residuals.

[17] There are other possible measures of a "family effect" in this case such as the average schooling level of the twins. The main findings of the paper are the same whether we control for the average education levels of the twins or the father's education level as our additional

though we follow Ashenfelter and Rouse (1998) in the parameterization of the endogeneity bias in this way, we do not parameterize the impact of the interaction between ability and education on earnings. The novelty of our approach relies precisely on the use of quantile regression techniques to explore this relationship based on the quantiles of wage residuals which we interpret as ability.

Figure 3 reports the results. Table 4A, panel A reports the returns to education for 19 quantiles 0.05 to 0.95 with 95% confidence bands for the specification including all covariates. Clearly, including the family effects has a substantial effect on the estimated returns. In general terms, the lines in Figure 3 are lower than the corresponding ones in Figure 1. This is consistent with the fact that we would expect part of the return to education to be absorbed by the family effect which reflects a positive endogeneity bias. Furthermore, the estimates of the endogeneity bias across different quantiles are in general monotonically increasing with τ though the precision of these estimates is poor[18]. This suggests that the findings of Buchinsky (1994) of higher returns to education at higher quantiles and to a lesser extent those of Mwabu and Schultz (1996) indeed reflect in part a differential endogeneity bias in schooling choices of individuals with different abilities rather than "true" differences in the marginal returns to education.

Nevertheless, it is quite clear from Figure 3 that in each specification, though the quantile curves of the estimated returns are flatter than in Figure 1, they are still generally increasing. Therefore, although differences across quantiles are, no doubt, less significant there still appears to be heterogeneity in the returns to education. This is strongly confirmed by the tests we report in Table 4B panel A. This is interesting given the fact that the precision of the estimates is worse now in the tails as reflected by the wider confidence bounds.

Hence, these findings suggest that differential endogeneity bias does not fully account for the patterns of heterogeneous increasing returns found in the base levels models. Some of this heterogeneity does seem to reflect actual differences in the market returns to schooling arising

regressor. In general, estimates which control for the average level of education of the twins are less precise. As in the OLS context, this approach has some similarities but is not equivalent to instrumenting the education level of each twin.

18 This is clearly due to the fact that the inclusion of father's education absorbs some of the variability in the own education variable for each twin.

from a complementary relationship between education and ability in enhancing earnings potential.

4.4 Family Effects Model With Instrumental Variables

The problem with the estimates from the previous section is that by including the mean education of the twins, the potential bias arising from measurement error in schooling levels is now aggravated. In this section we report the results of our fullest attempt to control for both the ability and the measurement errors biases. This is the direct analogue of section 4.3 except that we now use father's education level to instrument for education of the twins[19]. In Figure 4, which we call the "family effects" models with instrumental variables, the returns are quite sporadic. Note also that the confidence bands are very wide.

We report the actual returns and confidence intervals for the model with all variables in table 4, panel B. A comparison with the non IV estimates of the analogous family effect model indicates that the IV estimates are somewhat larger (consistent with a downward bias due to measurement error) but only in the lower tail of the distribution of wage residuals from quantiles up to 0.4. Although the family effect model with instruments (Fugure 4E) still suggests some mild heterogeneity in rerurns to education with higher returns at higher quantiles, the estimates are somewhat imprecise. In fact, when we test (Table 4B, panel B) for differences across quantiles, only in the case of comparing quantiles 0.25 and 0.4 are the returns significantly different (p-value = 0.0456) at 5 percent.

4.6 Estimation results for other Covariates

In this section we briefly describe the return to the other covariates included in our empirical model. Table 5 presents the returns to each of the variables for the "all" specification, which includes age, race, gender, married, union, and tenure, along with the associated confidence

[19] Here again we also used the average of the cross reports of the sibling's education to instrument for the average education of the twins. We found little difference. Even though this assumes the classical model of uncorrelated measurement error in sibling's education reports, in

intervals for the levels models. Table 6 does the same for the family effects models. Figure 7 is a concise summary of the results. It presents results for the family effects model without IV (also contained in Table 6, panel A). Note the anomalous negative effect of race on earnings which is also reported by Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998), but that this cannot be estimated with precision at any quantile. Also, the effect of marital status on earnings is positive but it is only significant at the median. The other three sets of results in the two tables are very similar to the findings depicted in Figure 7.

For most of the covariates, there is little heterogeneity in the returns, except for the female and union variables. Women in this sample earn about 18 percent less than men at low quantiles (0.1) but the gap widens to roughly 30 percent at higher quantiles (0.9)[20]. The returns to being covered by a union contract are also monotonically declining. At low quantiles (0.1) the return to being unionized is roughly 0.3 and at upper quantiles the return is roughly zero. This last result is consistent with the recent work that explores the effect of unions on the structure and the change in the distribution of wages[21].

5. Concluding Comments

In this paper we present estimates of a simple model of earnings and schooling choices in which we explicitly explore the relationship between education and genetic ability in the generation of human capital without imposing a stringent parametric structure on the relationship. We use recent data on identical twins to isolate the causal link between education and earnings while dealing with the well documented potential biases that arise from the correlation between ability and schooling investment choices and the fact that observed education levels are imperfect measures of schooling. To this end we use recent extensions of instrumental variables methods to quantile regression to estimate a whole family of returns to education at different quantiles of the conditional distribution of wages. We also make use of quantile regression based tests of heteroskedasticity to test for significant differences in these returns across quantiles.

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the event of correlated measurement errors the averaging reduces the inconsistency of the estimates.

20 The increased gap as quantiles increase is not consistent with Amidon (1997) who uses CPS data and finds small gaps in the tails and a large gap in the middle of the distribution.

21 We do not try to explain or discuss the implications of these findings here since the main focus of our paper is on heterogeneity in the returns to education. See DiNardo, Fortin, and

The results suggest the existence of an important upward ability bias in the estimates of the returns to education obtained from a model that does not account for the endogeneity of schooling choices. Nevertheless, the estimated returns to education accounting for the endogeneity of schooling are positive and significant consistent with the human capital model in which education enhances earnings potential. The results also suggest that the measurement error in schooling levels does not induce important downward biases in the estimated returns to education, but that these biases are intensified by attempts to deal with the ability bias. These findings are at odds with the early findings of Ashenfelter and Krueger (1994) based on a more restricted sample of twins data but are consistent with the more recent findings of Ashenfelter and Rouse (1998) which are based on the more extensive sample of data used in this paper.

More importantly, the results provide novel evidence of the existence of two sources of heterogeneity in the returns to education. First, there is strong evidence of a differential heterogeneity effect by which more able individuals become more educated because they face lower marginal costs of schooling. This induces an endogeneity bias at different quantiles in the estimates of the returns to education obtained from a model that does not "control" for unobservable ability. This quantile-specific endogeneity bias appears as apparent differences in the estimated returns to education across quantiles. In particular high-ability individuals appear to have higher returns to schooling.

Therefore, the earlier estimates of heterogeneous returns to schooling from quantile wage regressions that do not control for unobserved ability (Buchinsky (1994) and Mwabu and Schultz (1996)) may be confounding this differential endogeneity bias with any actual within quantile difference in the marginal returns to education.

Second, once this endogeneity bias is accounted for, our results provide significant evidence of the existence of actual heterogeneity in the market returns to education arising from a non-trivial interaction between schooling and unobservable individual ability. In particular, the evidence supports the existence of a complementary relationship between ability and education by which more able individuals have higher marginal returns to education. The results thus suggest that

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Lemieux (1996), and DiNardo and Lemieux (1997) for an interesting treatment of the effects of more able individuals attain more schooling because of the lower marginal costs they face and because of higher marginal benefits to each additional year of education.

These results are consistent with Buchinsky's (1994) reported estimates of returns to education that increase along the quantiles of the conditional wage distribution, though these do not control for ability or measurement error bias. On the other hand, our findings are inconsistent with the findings of Ashenfelter and Rouse (1997) of lower marginal returns for higher ability individuals after controlling for the endogeneity and measurement error in schooling. Nevertheless, as noted before, their estimate of the heterogeneity parameter is based on a full parameterization of the interaction between ability and education and is based on the estimation of a conditional mean wage function. This approach makes it more difficult to separately identify the effect of ability on the marginal benefit of schooling as reflected by the fact that their estimates are in general statistically insignificant.

Our results are consistent with Card's (1995a) proposition of a negative relationship between the marginal costs and the marginal returns to schooling along the distribution of abilities. Furthermore, we believe our findings provide unique empirical evidence to address two of the important questions carefully laid out in Card (1995a): "what is the causal effect of education?" and "is there evidence of individual heterogeneity in returns to education?". Overall, our results suggest that there is no unique causal effect of schooling and that for any particular individual the effect may be above or below the extensively documented OLS estimate depending on his or her ability. Our results thus reassure that any formal structural model of schooling investments and earnings should allow for potential heterogeneity in the returns to education (Card, 1995a) and perhaps diverse changes over time at different points in the wage distribution (Buchinsky, 1994, Chay and Lee, 1996).

There are several ways in which our work can be extended. First, a readily available extension is a careful exploration of potential differential effects of observable individual characteristics such as union participation and gender in the returns to education across quantiles of wage residuals. We expect to do this in subsequent work. Second, it would be interesting to explore potential non-linearities in the relationship between schooling and log-earnings by allowing the returns to

institutions (including unions) on the wage distribution.

education to differ across different education levels as in Buchinsky (1994) and Mwabu and Schultz (1996). Third, one could try to explore the impact that the changes over time in quantile estimates of the returns to education have on the structure of wages and widening wage inequality while carefully addressing the endogeneity and measurement error biases which are likely to change over time. This last point faces data limitations and some challenging but interesting unsolved methodological problems. There is a need to extend quantile regression methods to the analysis of panel data. In particular, an analogue of the fixed effects (differenced estimator) that is computationally feasible is called for.

Finally, the existence of the two sources of heterogeneity suggests that typical estimates of the mean return to education based on OLS provide a rather incomplete characterization of the impact of education on labor market outcomes and are thus a poor guide for public policy. On the one hand, the differential endogeneity bias that arises because of ability-based differences in the marginal costs of education imply that there is room for policies aimed at promoting heavier schooling investment by individuals that face higher costs. On the other hand, the indication that apart from this differential ability bias, the returns to schooling are higher for high-ability individuals suggests a limit on the extent to which schooling can compensate for differences in individual ability endowments. This all suggests that even though a general educational policy will tend to increase the welfare of individuals in the society, its net impact on the long run distribution of incomes and wealth will depend on the initial distribution of ability across the population.

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Table 1. MEANS, STANDARD ERRORS, AND MEDIANS

	Means	medians
education	14.13	14
	(0.07)	
age	37.75	36
	(0.39)	
white	0.92	1
	(0.01)	
female	0.58	1
	(0.02)	
Married	0.62	1
	(0.02)	
Union	0.21	0
	(0.01)	
Tenure	8.48	5
	(0.30)	

Source: Data are from Ashenfelter & Krueger (1991), Ashenfelter and Rouse (1998) and Rouse (1997). All dollar figures are in real 1995 dollars.

Notes: Standard errors are in parentheses. Sample size is 858.

TABLE 2. Estimates of the Return to Schooling

	Levels					Differences			
	(1) LS	(2) LS	(3) LS	(4) IV[b]	(5) IV[b]	(6) LS	(7) LS	(8) IV[c]	(9) A&KIV[d]
education	0.108	0.120	0.114	0.111	0.123	0.088	0.095	0.119	0.167
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.018)	(0.017)	(0.029)	(0.043)
age	0.099	0.087	0.089	0.099	0.087				
	(0.009)	(0.019)	(0.010)	(0.009)	(0.010)				
$(age)^2$	-0.001	-0.001	-0.001	-0.001	-0.001				
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)				
female	-0.335	-0.266	-0.266	-0.334	-0.265				
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)				
white	-0.079	-0.096	-0.108	-0.078	-0.095				
	(0.063)	(0.060)	(0.060)	(0.063)	(0.060)				
married		0.080	0.082		0.084		0.012	0.016	
		(0.044)	(0.044)		(0.044)		(0.066)	(0.066)	
union		0.099	0.103		0.100		0.074	0.076	
		(0.042)	(0.042)		(0.042)		(0.052)	(0.052)	
tenure		0.020	0.020		0.020		0.019	0.019	
		(0.002)	(0.002)		(0.002)		(0.003)	(0.003)	
father's educ			0.013						
			(0.006)						
N	858	858	858	858	858	429	429	429	149
R^2	0.339	0.395	0.397			0.052	0.128		

Notes: (a) The difference in education is the difference between the first twin's report of twin one and the second twin's report of twin 2.

(b) The instrument used is the twin's report of one's own education.

(c) The instrument used in these analyses is twin 1's report of twin 2's education minus twin 2's report of twin 1's education.

(d) From Ashenfelter and Krueger (1994). Our sample size differs from Ashenfelter & Krueger (1994) as we use an extract from Rouse (1997) which includes three additional years of the Princeton Twins Data. Rouse (1997) carefully points out that although she finds " ... the return to schooling among identical twins is around 10-12 percent per year of school completed ... Ashenfelter and Krueger's estimates are insignificantly different ..."

TABLE 3A. LEVELS MODEL: QUANTILE REGRESSION ESTIMATES, WITH AND WITHOUT INSTRUMENTAL VARIABLES

Quantile	Panel A: Levels Model Without Instrumental Variables			Panel B: Levels Model With Instrumental Variables		
	lower bound	return estimate	upper bound	lower bound	return estimate	upper bound
0.05	0.0698	0.0363	0.1149	0.0742	-0.0382	0.1865
0.10	0.0869	0.0249	0.1105	0.0690	0.0114	0.1266
0.15	0.0818	0.0640	0.1048	0.0920	0.0521	0.1318
0.20	0.0872	0.0699	0.1084	0.0958	0.0637	0.1279
0.25	0.1013	0.0795	0.1227	0.1202	0.0976	0.1427
0.30	0.1090	0.0920	0.1269	0.1191	0.1003	0.1379
0.35	0.1097	0.0974	0.1309	0.1160	0.0990	0.1330
0.40	0.1186	0.1014	0.1329	0.1178	0.0995	0.1362
0.45	0.1238	0.1090	0.1403	0.1268	0.1093	0.1443
0.50	0.1303	0.1130	0.1428	0.1274	0.1111	0.1436
0.55	0.1340	0.1148	0.1428	0.1342	0.1177	0.1506
0.60	0.1339	0.1179	0.1483	0.1348	0.1177	0.1519
0.65	0.1333	0.1201	0.1442	0.1389	0.1204	0.1574
0.70	0.1322	0.1190	0.1491	0.1361	0.1146	0.1577
0.75	0.1343	0.1121	0.1486	0.1315	0.1064	0.1567
0.80	0.1265	0.1121	0.1399	0.1237	0.0924	0.1550
0.85	0.1336	0.1149	0.1482	0.1232	0.0826	0.1637
0.90	0.1391	0.1088	0.1657	0.1299	0.0729	0.1870
0.95	0.1363	0.1102	0.1773	0.1396	-0.0198	0.2989

Note: These are the estimates which are contained in FIGURE 1E and FIGURE 2E, respectively. The other independent variables we control for are age, age^2, race, gender, married, union, and tenure. Testing for equality of returns at various quantiles – testing for heterogeneity – is done in TABLE 3B.

TABLE 3B. LEVELS MODEL: TESTS OF EQUALITY OF RETURNS TO SCHOOLING FOR QUANTILE REGRESSION ESTIMATES, WITH AND WITHOUT INSTRUMENTAL VARIABLES

		Panel A: Levels Model without Instrumental Variables		Panel B: Levels Model with Instrumental Variables	
quantiles		t-statistic	p-value	t-statistic	p-value
0.10	0.25	0.0786	0.7793	0.0131	0.9088
0.10	0.40	3.2112	0.0731	2.2727	0.1317
0.10	0.50	5.8218	0.0158	2.4524	0.1173
0.10	0.60	5.8600	0.0155	4.0262	0.0448
0.10	0.75	5.3746	0.0204	2.7266	0.0987
0.10	0.90	4.7411	0.0294	1.5828	0.2084
0.25	0.40	6.4846	0.0109	4.5685	0.0326
0.25	0.50	10.5326	0.0012	4.7471	0.0293
0.25	0.60	10.8578	0.0010	7.3187	0.0068
0.25	0.75	8.1182	0.0044	4.3845	0.0363
0.25	0.90	5.2841	0.0215	2.3446	0.1257
0.40	0.50	2.7590	0.0967	0.1444	0.7040
0.40	0.60	2.1231	0.1451	1.3208	0.2505
0.40	0.75	1.4341	0.2310	0.3021	0.5826
0.40	0.90	1.2874	0.2565	0.0593	0.8077
0.50	0.60	0.0150	0.9024	1.1124	0.2916
0.50	0.75	0.0394	0.8426	0.0988	0.7532
0.50	0.90	0.2581	0.6114	0.0044	0.9473
0.60	0.75	0.0213	0.8840	0.2581	0.6115
0.60	0.90	0.2319	0.6301	0.1742	0.6764
0.75	0.90	0.1980	0.6564	0.0241	0.8766

Note: This table corresponds to Table 3A which presents estimated returns to schooling for the levels model with andwithout instrumental variables. These tests (and TABLE 3A) correspond to FIGURES 1E and 2E. The other independent variables we control for are age, age^2, race, gender, married, union, and tenure

TABLE 4A. FAMILY EFFECTS MODEL: QUANTILE REGRESSION ESTIMATES, WITH AND WITHOUT INSTRUMENTAL VARIABLES

Quantile	Panel A: Family Effect Model Without Instrumental Variables			Panel B: Family Effect Model With Instrumental Variables		
	lower bound	return estimate	upper bound	lower bound	return estimate	upper bound
0.05	0.0702	0.0347	0.1178	0.0867	-0.0321	0.2055
0.10	0.0853	0.0347	0.1083	0.0677	0.0066	0.1288
0.15	0.0798	0.0653	0.1015	0.0927	0.0541	0.1312
0.20	0.0878	0.0651	0.1068	0.0961	0.0638	0.1284
0.25	0.0989	0.0805	0.1204	0.1193	0.0939	0.1446
0.30	0.1135	0.0913	0.1227	0.1189	0.0985	0.1393
0.35	0.1092	0.0942	0.1332	0.1145	0.0944	0.1345
0.40	0.1108	0.0969	0.1323	0.1130	0.0935	0.1326
0.45	0.1216	0.1030	0.1337	0.1221	0.1039	0.1404
0.50	0.1213	0.1096	0.1403	0.1221	0.1040	0.1402
0.55	0.1276	0.1100	0.1383	0.1253	0.1078	0.1429
0.60	0.1291	0.1072	0.1430	0.1289	0.1115	0.1464
0.65	0.1278	0.1150	0.1417	0.1250	0.1063	0.1436
0.70	0.1281	0.1099	0.1461	0.1309	0.1074	0.1543
0.75	0.1234	0.1071	0.1432	0.1307	0.1012	0.1603
0.80	0.1221	0.1041	0.1370	0.1151	0.0813	0.1490
0.85	0.1209	0.1070	0.1345	0.1037	0.0614	0.1460
0.90	0.1273	0.1009	0.1458	0.1035	0.0407	0.1663
0.95	0.1261	0.0962	0.1435	0.1291	-0.0264	0.2846

Note: These are the estimates which are contained in FIGURE 3E and FIGURE 4E, respectively. The other independent variables we control for are age, age^2, race, gender, married, union, and tenure. Testing for equality of returns at various quantiles – testing for heterogeneity – is done in TABLE 4B.

TABLE 4B. FAMILY EFFECTS MODELS: TESTS OF EQUALITY OF RETURNS TO SCHOOLING FOR QUANTILE REGRESSION ESTIMATES, WITH AND WITHOUT INSTRUMENTAL VARIABLES

		Panel A: Family Model without Instrumental Variables		Panel B: Family Model with Instrumental Variables	
quantiles		t-statistic	p-value	t-statistic	p-value
0.10	0.25	0.0125	0.9109	0.0477	0.8272
0.10	0.40	2.2160	0.1366	1.8157	0.1778
0.10	0.50	3.5899	0.0581	1.5928	0.2069
0.10	0.60	4.4499	0.0349	1.4776	0.2242
0.10	0.75	4.1529	0.0416	2.3301	0.1269
0.10	0.90	2.4927	0.1144	0.0640	0.8003
0.25	0.40	7.1765	0.0074	3.9971	0.0456
0.25	0.50	8.4828	0.0036	2.9040	0.0884
0.25	0.60	9.2836	0.0023	2.5983	0.1070
0.25	0.75	7.4266	0.0064	3.5512	0.0595
0.25	0.90	3.6078	0.0575	0.1807	0.6708
0.40	0.50	1.1163	0.2907	0.0152	0.9019
0.40	0.60	1.8903	0.1692	0.0098	0.9210
0.40	0.75	1.2116	0.2710	0.2918	0.5891
0.40	0.90	0.4400	0.5071	0.8283	0.3628
0.50	0.60	0.4301	0.5119	0.0000	0.9983
0.50	0.75	0.2408	0.6237	0.4922	0.4829
0.50	0.90	0.0645	0.7995	0.7518	0.3859
0.60	0.75	0.0030	0.9565	0.6366	0.4249
0.60	0.90	0.0010	0.9743	0.8467	0.3575
0.75	0.90	0.0049	0.9443	2.4279	0.1192

Note: This table corresponds to Table 4A which presents estimated returns to schooling for the levels model with andwithout instrumental variables. These tests (and TABLE 4A) correspond to FIGURES 3E and 4E. The other independent variables we control for are age, age^2, race, gender, married, union, and tenure.

TABLE 5. LEVELS MODELS: QUANTILE REGRESSION ESTIMATES FOR ALL VARIABLES

PANEL A: LEVELS MODEL WITHOUT INSTRUMENTS

	0.10	0.25	0.50	0.75	0.90
education	0.090	0.094	0.131	0.133	0.140
	(0.055,0.105)	(0.083,0.109)	(0.115,0.146)	(0.113,0.153)	(0.106,0.166)
age	0.081	0.094	0.091	0.088	0.063
	(0.058,0.106)	(0.071,0.106)	(0.074,0.106)	(0.060,0.124)	(0.027,0.118)
$(age)^2$	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.000)
female	-0.182	-0.204	-0.212	-0.277	-0.351
	(-0.248,-0.065)	(-0.266,-0.135)	(-0.269,-0.167)	(-0.344,-0.201)	(-0.521,-0.197)
white	-0.066	-0.136	-0.106	-0.097	-0.150
	(-0.263,0.060)	(-0.208,0.020)	(-0.205,-0.004)	(-0.302,0.032)	(-0.336,0.056)
union	0.296	0.164	0.056	0.082	-0.020
	(0.197,0.368)	(0.094,0.231)	(0.005,0.138)	(-0.024,0.136)	(-0.145,0.087)
married	0.116	0.036	0.067	0.075	0.112
	(-0.058,0.214)	(-0.016,0.150)	(-0.003,0.143)	(-0.027,0.161)	(-0.090,0.187)
tenure	0.017	0.023	0.021	0.019	0.021
	(0.014,0.021)	(0.020,0.027)	(0.017,0.025)	(0.013,0.026)	(0.013,0.032)
intercept	-0.996	-0.900	-1.166	-0.848	-0.081
	(-1.540,-0.196)	(-1.293,-0.405)	(-1.507,-0.923)	(-1.412,-0.400)	(-1.079,0.909)

PANEL B: LEVELS MODEL WITH INSTRUMENTS

	0.10	0.25	0.50	0.75	0.90
education	0.100	0.098	0.128	0.132	0.129
	(0.045,0.154)	(0.074,0.121)	(0.110,0.146)	(0.107,0.156)	(0.073,0.185)
age	0.093	0.085	0.092	0.096	0.066
	(0.036,0.150)	(0.061,0.110)	(0.073,0.110)	(0.070,0.123)	(0.007,0.125)
$(age)^2$	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.002,-0.000)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,0.000)
female	-0.153	-0.206	-0.224	-0.263	-0.354
	(-0.359,0.054)	(-0.296,-0.116)	(-0.291,-0.156)	(-0.358,-0.168)	(-0.567,-0.142)
white	-0.116	-0.130	-0.123	-0.112	-0.131
	(-0.468,0.237)	(-0.284,0.023)	(-0.239,0.008)	(-0.275,0.050)	(-0.495,0.233)
union	0.272	0.172	0.065	0.014	-0.002
	(0.023,0.521)	(0.063,0.281)	(-0.017,0.146)	(-0.101,0.129)	(-0.259,0.255)
married	0.056	0.075	0.098	0.067	0.088
	(-0.205,0.316)	(-0.039,0.188)	(0.013,0.183)	(-0.054,0.187)	(-0.180,0.357)
tenure	0.018	0.024	0.021	0.018	0.019
	(0.004,0.033)	(0.018,0.030)	(0.016,0.025)	(0.011,0.024)	(0.004,0.034)
intercept	-1.318	-0.813	-1.116	-0.981	0.045
	(-2.646,0.011)	(-1.391,-0.234)	(-1.550,-0.681)	(-1.594,-0.369)	(-1.324,1.413)

TABLE 6. "FAMILY EFFECTS" MODELS: QUANTILE REGRESSION ESTIMATES FOR ALL VARIABLES

PANEL A: "FAMILY EFFECTS" MODEL WITHOUT INSTRUMENTS

	0.10	0.25	0.50	0.75	0.90
education	0.092	0.090	0.122	0.127	0.126
	(0.054,0.102)	(0.077,0.108)	(0.108,0.145)	(0.108,0.142)	(0.106,0.150)
father's	0.004	0.004	0.009	0.017	0.033
education	(-0.008,0.016)	(-0.007,0.017)	(-0.002,0.018)	(0.007,0.023)	(0.014,0.047)
age	0.083	0.096	0.096	0.087	0.071
	(0.057,0.107)	(0.071,0.112)	(0.076,0.111)	(0.067,0.108)	(0.035,0.108)
$(age)^2$	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.000)
female	-0.178	-0.207	-0.227	-0.266	-0.313
	(-0.248,-0.087)	(-0.266,-0.140)	(-0.278,-0.157)	(-0.337,-0.212)	(-0.454,-0.195)
white	-0.083	-0.136	-0.124	-0.090	-0.206
	(-0.265,0.071)	(-0.215,0.017)	(-0.203,-0.029)	(-0.307,0.023)	(-0.382,0.010)
union	0.298	0.169	0.058	0.058	0.027
	(0.204,0.367)	(0.088,0.229)	(-0.026,0.144)	(-0.001,0.135)	(-0.105,0.175)
married	0.117	0.041	0.060	0.080	0.100
	(-0.046,0.213)	(-0.033,0.150)	(0.009,0.128)	(-0.033,0.152)	(-0.101,0.205)
tenure	0.016	0.023	0.020	0.019	0.021
	(0.014,0.021)	(0.019,0.027)	(0.014,0.024)	(0.012,0.027)	(0.012,0.030)
intercept	-1.072	-0.925	-1.227	-0.969	-0.419
	(-1.655,-0.093)	(-1.349,-0.424)	(-1.519,-0.888)	(-1.332,-0.668)	(-1.288,0.571)

PANEL B: "FAMILY EFFECTS" MODEL WITH INSTRUMENTS

	0.10	0.25	0.50	0.75	0.90
education	0.101	0.098	0.123	0.131	0.107
	(0.045,0.158)	(0.072,0.124)	(0.104,0.141)	(0.101,0.161)	(0.046,0.168)
father's	-0.003	-0.001	0.011	0.010	0.041
education	(-0.043,0.038)	(-0.019,0.018)	(-0.003,0.024)	(-0.012,0.032)	(-0.003,0.085)
age	0.092	0.086	0.095	0.095	0.064
	(0.037,0.147)	(0.061,0.111)	(0.076,0.113)	(0.065,0.125)	(0.004,0.124)
$(age)^2$	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.002,-0.000)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,-0.001)	(-0.001,0.000)
female	-0.156	-0.204	-0.220	-0.262	-0.319
	(-0.354,0.042)	(-0.295,-0.114)	(-0.286,-0.155)	(-0.369,-0.155)	(-0.535,-0.103)
white	-0.102	-0.131	-0.134	-0.123	-0.104
	(-0.443,0.239)	(-0.286,0.024)	(-0.247,-0.021)	(-0.307,0.061)	(-0.476,0.268)
union	0.275	0.170	0.086	0.013	0.059
	(0.036,0.515)	(0.061,0.279)	(0.007,0.166)	(-0.116,0.143)	(-0.202,0.321)
married	0.056	0.072	0.087	0.063	0.040
	(-0.195,0.306)	(-0.042,0.186)	(0.004,0.170)	(-0.072,0.198)	(-0.233,0.312)
tenure	0.018	0.024	0.019	0.018	0.020
	(0.004,0.032)	(0.018,0.031)	(0.015,0.024)	(0.010,0.026)	(0.004,0.035)
intercept	-1.289	-0.814	-1.237	-1.077	-0.218
	(-2.602,0.023)	(-1.412,-0.216)	(-1.671,-0.802)	(-1.786,-0.368)	(-1.650,1.215)