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Omar Arias

*Inter-American Development Bank*

Kevin F. Hallock

*Cornell University, [kfh7@cornell.edu](mailto:kfh7@cornell.edu)*

Walter Sosa-Escudero

*Universidad Nacional de la Plata*

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# Individual Heterogeneity in the Returns to Schooling: Instrumental Variables Quantile Regression Using Twins Data

## Abstract

Considerable effort has been exercised in estimating mean returns to education while carefully considering biases arising from unmeasured ability and measurement error. Recent work has investigated whether there are variations from the “mean” return to education across the population with mixed results. We use an instrumental variables estimator for 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 test whether there is individual heterogeneity in returns to education and find that: more able individuals obtain more schooling and that higher ability individuals (those further to the right in the conditional distribution of wages) have higher returns to schooling consistent with a non-trivial interaction between schooling and unobserved abilities in the generation of earnings. The estimated returns are never lower than 9 percent and can be as high as 13 percent at the top of the conditional distribution of wages but they vary significantly only along the lower to middle quantiles. Our findings may have meaningful implications for the design of educational policies.

## Keywords

returns to education, human capital, heterogeneity, quantile treatment effects, instrumental variables

## Disciplines

Higher Education | Labor Relations

## Comments

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# Individual heterogeneity in the returns to schooling: instrumental variables quantile regression using twins data\*

Omar Arias<sup>1</sup>, Kevin F. Hallock<sup>2</sup>, Walter Sosa-Escudero<sup>3</sup>

<sup>1</sup> Inter-American Development Bank, 1300 New York Ave., NW, STOP E-0421, Washington, DC 20577 (email: omara@iadb.org)

<sup>2</sup> Department of Economics, University of Illinois, 1206 South 6th Street, Champaign, IL 61820 (email: hallock@uiuc.edu)

<sup>3</sup> Department of Economics, Universidad Nacional de la Plata, La Plata, Argentina (email: wsosa@feedback.net.ar)

**Abstract.** Considerable effort has been exercised in estimating mean returns to education while carefully considering biases arising from unmeasured ability and measurement error. Recent work has investigated whether there are variations from the “mean” return to education across the population with mixed results. We use an instrumental variables estimator for 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 test whether there is individual heterogeneity in returns to education and find that: more able individuals obtain more schooling perhaps due to lower marginal costs and/or higher marginal benefits of schooling and that higher ability individuals (those further to the right in the conditional distribution of wages) have higher returns to schooling consistent with a non-trivial interaction between schooling and unobserved abilities in the generation of earnings. The estimated returns are never lower than 9 percent and can be as high as 13 percent at the top of the conditional distribution of wages but they vary significantly only along the

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lower to middle quantiles. Our findings may have meaningful implications for the design of educational policies.

**Key words:** Returns to Education, Human Capital, Heterogeneity, Quantile Treatment Effects, Instrumental Variables.

**JEL classification:** C14, I2, J24, J31

## 1. Introduction

The causal relation between education and earnings has been one of the most heavily and carefully explored subjects in empirical work in labor economics (See Card (1999) for a comprehensive review). 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 is that it is difficult to isolate the 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 related to schooling. More specifically, failure to account for the effect of unobserved “abilities” or family background factors on both earnings and attained schooling levels may lead to incorrect inferences regarding the causal effect of education.

There are important reasons why economists and policy makers are interested in obtaining accurate measures of the earnings premium associated with acquiring more education. From a “private” point of view, under certain conditions, it provides a measure of the “return” to investment in additional schooling. 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.<sup>1</sup>

In this paper we investigate whether people with different levels of “ability” obtain different returns to education. Specifically, we provide unique empirical evidence to address two important questions carefully laid out by Card (1995a): “what is the causal effect of education?” and “is there evidence of individual heterogeneity in returns to education?”

Our concept of “ability” refers to those marketable unobservable factors that make up an individual’s initial endowment of human capital and translate into higher earnings. These may vary across families as well as individuals. This follows Griliches (1977) and differs from the view of ability as “IQ”, for which measures can be constructed using test scores. Most studies estimate the mean return to education which may be interpreted as the return for an individual with mean ability. This is a sensible characterization when the return to education is constant across levels of (unobserved) ability or when any increase in schooling has a similar effect on earnings of observationally identical individuals. In this case, ability and education do not interact in the generation of human capital; both factors have independent contributions to the accumulated stock.

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<sup>1</sup> See Psacharopoulos and Ng (1994) for a cost-benefit formulation. The macro-evidence on the impact of more education on economic growth is controversial (see for example Pritchett, 1997).

Instead we investigate whether education induces a more intricate change in the distribution of earnings rather than a pure location shift. We take education and ability as two separate factors in the generation of human capital which interact in a non-trivial, unknown way. On the one hand, if ability and education are substitutes in the generation of human capital, then we might expect marginal returns to the accumulation of human capital to decrease with ability and hence education contributes relatively more to low ability individuals. On the other hand, if ability and education are complements in the generation of human capital, then education has an additional indirect effect on human capital (through the interaction with ability) that increases its otherwise constant contribution to earnings. Returns would then be higher for the more able. In the language of the empirical literature on program evaluation, in these cases the response to the treatment (education) varies across individuals and the mean return to education may be an incomplete summary of a richer pattern of ways that education affects people's earnings.

In exploring this issue we face several methodological and empirical limitations. First, it is well known that available measures of "ability" such as IQ suffer from biases that reflect prior education and family background. Furthermore, these do not necessarily capture the type of "abilities" that enhance earnings potential. Therefore, for the purposes of this paper we must proceed without observing ability and hence we cannot model its relationship with education explicitly by including additional regressors based on interaction effects. Besides, 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. In the above examples, the return to education would be a monotonic function of the level of ability, but we see no reason to impose such a restriction. We want our empirical model to be exploratory and informative about the nature of this relationship. Second, education is not randomly assigned to individuals so we cannot treat the attained level of education as a predetermined variable. The optimal level of education is likely determined endogenously as a function of the level of ability and other factors such as family background. 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 additional biases in conventional estimates that do not account for this possibility.

The interaction between ability and education studied in this paper 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. Ashenfelter and Rouse (1998) analyze an expanded version (two additional years) of the sample of genetically identical twins used in Ashenfelter and Krueger (1994) which followed from the earlier research of Behrman et al. (1980). Ashenfelter and Krueger (1994) exploit the presumed similarity of twins and the availability of multiple measures of schooling to explicitly model the link between family ability and education parametrically, while addressing the measurement error and endogeneity biases using standard panel data methods. They find some evidence of the existence of a negative relationship between ability and returns to education, suggesting that less able individuals benefit more from additional schooling. Conneely and Uusitalo (1998) also investigate the question of heterogeneous returns in the context of a random coefficients

model of wage determination. They use data on ability test scores and family background variables on a sample of Finnish men and parameterize potential heterogeneity in the mean return to education by interacting these factors with education. They find stronger evidence of variations in returns to education most of which, nevertheless, cannot be explained by observable individual heterogeneity.

We believe these fully parametric approaches impose strong restrictions on the structure of heterogeneity in returns to education. In this paper we use instrumental variables quantile regression methods on an expanded sample of 858 genetically identical twins from that analyzed by 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 we view as reflecting the distribution of unobservable ability. Unlike the above approaches which explicitly concentrate on the effect of education on the conditional mean of earnings and parameterize variations in returns through proxies for ability, quantile techniques allow us to freely characterize the effect of education on the whole conditional distribution of earnings. That is, we focus on the quantile treatment effects of education on earnings rather on average treatment effects. Our approach is semiparametric in the sense that it imposes relatively weak parametric structure on the relationship between earnings and education. Minimal structure is imposed on the key relationship of interest: the interaction between education and ability in the generation of earnings. We use testing procedures based on quantile regression statistics to formally test for the presence of heterogeneity in the returns to education.

Although he does not treat the ability-education interaction explicitly, Buchinsky's (1994) analysis of the U.S. wage structure, using Current Population Survey (CPS) data and censored quantile regression methods, shows that returns to education in the U.S. increase dramatically over the quantiles of the conditional distribution of wages. Mwabu and Schultz (1996) also use quantile methods on a sample of South African men and obtain varying returns across quantiles that they interpret along the lines explored in this paper. Similar quantile results were found by Fitzenberger and Kurz (1998) in a study of earnings in Germany and by Machado and Mata (2000) in a study of wage inequality in Portugal. Nevertheless, the results of these studies should be interpreted with caution since they do not handle the problems of measurement error or endogeneity bias. The finding of heterogeneous returns may simply reflect a variable ability-based endogeneity bias: more able individuals, facing lower marginal costs of schooling, choose to acquire more education and appear to have higher marginal returns to education.

The availability of twins data (with multiple measures of schooling) allows us to deal with the endogeneity of education arising from measurement error while indirectly controlling for any ability bias arising from "family effects". (As explained in more detail below, the use of standard panel data methods in a quantile regression context introduces some complications). As in all the other previous twins literature, our estimates rely crucially on the assumption that any ability bias is due to unobservable family factors. In a recent paper, Bound and Solon (1999) criticize the estimates of returns to education based on twins data questioning the validity of this assumption. If schooling and the individual component of the error term in the wage equation are positively correlated, then our estimates can be thought to provide a set of upper bounds on the causal effect of education on earnings.

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 unobserved heterogeneity. In section 3 we outline our empirical framework. Section 4 briefly describes the data and discusses previous estimates of the mean return to schooling. In section 5, we present the details of model specification, estimation, develop tests for heterogeneity in returns to schooling, and discuss the results. Section 6 discusses policy implications of our findings and concludes.

## 2. A model of earnings, schooling, and ability

Following Ashenfelter and Rouse (1998) and Card (1995a), we lay out a simple structural model based on the Becker (1967) model of investment in education focusing on the following questions: 1) How can we think about the link between earnings, ability and education? 2) Are returns to education homogeneous across the population? 3) If not, why is quantile regression an appropriate tool to explore the source of this heterogeneity? 4) How can we exploit twins data to deal with measurement error in schooling, and ability bias in the quantile regression framework?

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

$$\max_{S_{ij}} U(Y_{ij}, S_{ij}) = \ln(y_{ij}(S_{ij}, A_j, \varepsilon_{ij})) - h_j(S_{ij}, r_j) \quad (1)$$

The first term consists of a human capital production function which receives as inputs education ( $S_{ij}$ ), an unobservable, family specific, “ability” variable ( $A_j$ ), and a random idiosyncratic disturbance ( $\varepsilon_{ij}$ ) from a continuous distribution  $f_\varepsilon$ . This term captures the interaction between education, ability and the idiosyncratic shock in the generation of earnings ( $Y_{ij}$ ). The second term measures the explicit and implicit (opportunity) costs of education and depends on education ( $S_{ij}$ ) and family specific factors ( $r_j$ ) such as wealth or tastes for education. We think of ( $A_j$ ) as a measure of unobservable “family effects” that cause individuals from different families to have different earnings. These “family effects” could originate from differences in family specific human capital (e.g., genetic intelligence, early learning environments), quality of schooling and/or labor market connections.<sup>2</sup> The idiosyncratic component  $\varepsilon_{ij}$  may capture differences in individual specific ability and risk taking that lead to earnings differences among twins from the same family.

The optimal schooling choice of a twin in the  $j$ -th family strikes a balance between the marginal benefits and costs of additional schooling given his or her endowment of ability and family background. If utility is globally concave in ( $S_{ij}$ ), there will be a unique level of education  $S_{ij}^* = S_{ij}(A_j, r_j, \varepsilon_{ij})$  that solves (1). Thus, schooling choices can potentially differ both among individuals of different families (due to family factors), and between twins from the same family (due to the idiosyncratic earnings disturbance). This is the source of the

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<sup>2</sup> Differences in schooling quality are most relevant across families since twins often go to the same school.

well-known endogeneity or ability bias that has historically haunted estimates of the returns to schooling. Griliches (1977, 1979) lucidly discussed the acute problems that the potential correlation between  $(A_j, r_j, \varepsilon_{ij})$  and the observed choices of  $(S_{ij})$  pose to the estimation of even the simplest linear earnings functions.

The main advantage of using data on earnings and education from a sample of twins to estimate the returns to schooling comes from exploiting the common components of the unobservable ability variable across twins. Let  $v_{ij} = \gamma A_j + \varepsilon_{ij}$ . This corresponds to our concept of “ability” or market ability. A simple specification, which is an extension of Rosen (1973), that allows us to highlight the important issues is

$$U(Y_{ij}, S_{ij}) = \beta_0 S_{ij} + \phi(S_{ij}, v_{ij}) + v_{ij} - [r_j S_{ij} + 0.5cS_{ij}^2]$$

where the first three terms represent the earnings function and the terms in brackets represent the anti-log of the cost function. Then, a necessary condition for a maximum interior solution is:

$$MB_{ij} \equiv \beta_{ij} \equiv \beta_0 + \phi_{S_{ij}} = MC_{ij} \equiv r_j + cS_{ij} \quad (2)$$

where  $\phi_{S_{ij}}$  is the derivative of  $\phi$  with respect to  $(S_{ij})$ . Sufficient conditions are that  $MB_{ij} > 0$ ,  $MC_{ij} > 0$  and  $0 < \frac{\partial MC_{ij}}{\partial S_{ij}} > \frac{\partial MB_{ij}}{\partial S_{ij}}$ , that is:  $\beta_{ij} > r_j > 0$ ,  $c > \phi_{ss} \geq 0$ . The function  $\phi$  captures the effect of ability on the rate of human capital accumulation, in a sense similar to Griliches (1977, p. 17) when he states “If ability is interpreted as implying different ex-ante  $\beta$ s, then there should be an interaction between the schooling and ability measures in the earnings equation.”  $(\beta_{ij})$  is interpreted as the return to an additional year of schooling (Becker, 1967) or as the “treatment effect” of schooling on wages in the recent program evaluation literature. It may depend on the level of education and on unobservable ability.

As discussed by Ashenfelter and Rouse (1998), in order to identify  $(\beta_{ij})$  from within-family variation in schooling levels, we need to assume that:

$$S_{ij}^* = S_j^* + u_{ij} \quad (3)$$

where the  $u_{ij}$  are *iid* errors over  $i$  and  $j$  from a continuous distribution function  $f_u$ , and are independent of the  $(\varepsilon_{ij})$  and  $(S_j^*)$ . That is, we assume that any differences in schooling between twins of the same family are due to optimization or measurement errors that are uncorrelated with the idiosyncratic earnings disturbance. Thus, any within-twins difference in the marginal benefit of schooling does not affect their optimal schooling choices. This would occur if the choice of  $(S_{ij}^*)$  is based on the expected average return to education due to uncertainty about the market wage premium for individual abilities. Thus, although individuals have better information than the econometrician, it is still imperfect. Recently, Bound and Solon (1999) questioned the plausibility of assumption (3). Nevertheless, using the same data used in this work, Ashenfelter and Rouse (1998) conducted a variety of tests which support the



hypothesis that twins' schooling choices are uncorrelated with unobservable determinants of individual earnings.<sup>3</sup>

Note that (2)–(3) imply that systematic differences in observed schooling levels in the population arise from two sources. First, individuals may have different returns to schooling (due to different  $v_{ij}$ ). Assuming differentiability in (2) at the optimal level of schooling we have that:

$$\frac{\partial \ln(Y_{ij})}{\partial S_{ij} \partial v_{ij}} = \frac{\partial MB_{ij}}{\partial v_{ij}} = \phi_{S_{ij}, v_{ij}} \quad (4)$$

where  $\phi_{S,v}$  denotes the cross-partial second derivative of  $\phi$  with respect to ( $S_{ij}$ ) and ( $v_{ij}$ ). This captures how ability affects the return to education. As long as  $\phi_{S,v} \neq 0$  the return to education will vary across individuals (of the same education level). Differing abilities alter returns so that there exists a family of returns to education. This is precisely what we mean by heterogeneity in the returns to schooling. The standard specification and estimation of Mincer equations assumes  $\phi_{S,v} = 0$  implicitly which implies that education and ability are “perfect substitutes” in the production of human capital. If  $\phi_{S,v} > 0$  for all  $v$  ability enhances the wage gains of acquiring an additional year of education, while if  $\phi_{S,v} < 0$  high ability individuals face lower returns to investment in education. Both cases are possible since we do not need to require  $\phi_S$  to be monotonic in ( $v_{ij}$ ).

Second, individuals may have different marginal rates of substitution between schooling and future earnings ( $r_j$ ) due to differences in the implicit marginal costs of schooling. For the utility specification considered we have that at  $S_{ij}^*$ :

$$\frac{\partial^2 U_{ij}}{\partial S_{ij} \partial A_j} = \phi_{S,A} - \frac{\partial r_j}{\partial A_j} \quad (5)$$

which determines the rate at which an individual of the same family can substitute (family) ability and education to generate a given level of utility. Since higher ability parents tend to acquire more education and have higher earnings, the second term in the right-hand side may capture differences in wealth or tastes for education across families. We expect ( $A_j$ ) to be negatively correlated with ( $r_j$ ) since individuals from wealthier and/or more able families presumably face lower opportunity costs of schooling. When (5) is negative the marginal rate of substitution between ability and education is decreasing in ability: schooling compensates more the less able for their less favorable genetic endowments. The opposite is true if  $\phi_{S,A} > 0$ . In this case variations in the returns to education across families amplify the ability (selection) bias by which the more able obtain more education.

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<sup>3</sup> For instance, when asked why they have attained different schooling only 11% of the twins reported reasons that might suggest within twins ability differences. In addition, 60% of the variability in schooling choices is due to differences across families, and potential non-genetic differences in ability between twins (such as birth order) are not significantly correlated with earnings.

### 3. The empirical framework

Integration of  $MB_{ij}$  over  $S_{ij}$  yields the log-linear earnings function known as the Mincer equation (Mincer, 1974) for which we adopt the following empirical specification:

$$\ln(Y_{ij}) = \alpha F_j + \lambda X_{ij} + \beta_0 S_{ij} + \phi(S_{ij}, v_{ij}) + v_{ij} \quad (6)$$

where  $(F_j)$  groups family specific variables (age, race),  $(X_{ij})$  captures twin specific characteristics other than education (union participation, tenure, marital status), and  $(\alpha, \lambda, \gamma, \beta)$  are the coefficients.

Equations (3) and (6) determine the joint distribution of earnings and education. We use (6) to estimate the returns to schooling using twins data on wages and education while taking into account four features of empirical measurements from this distribution: i) the “stylized” log-linear relationship between wages and education, ii) heterogeneity in the distribution of earnings conditional on education, iii) the endogeneity of observed education levels due to unobservable ability and family factors, and iv) measurement error in reported schooling choices.

The log-linearity of education-earnings profiles is one of the most remarkable empirical regularities documented in labor economics. Heckman and Polachek (1974), Card and Krueger (1992), and Park (1994) all provide supporting evidence. Park (1994) actually found log-linearity to be a fairly good approximation of the earnings-schooling relationship for several quantiles of the earnings distribution. Existing evidence points to only slight deviations from log-linearity. In particular, Park’s work and work by Solon and Hungerford (1987), Jaeger and Page (1996) and Heckman et al (1996) find evidence consistent with the existence of “sheepskin” (credentialling) type effects for college graduation. Unfortunately, in our case, the examination of such effects or concavity in the earnings-schooling profile would make estimating earnings equations intractable because of the problems associated with estimation of an equation with an endogenous quadratic term or endogenous dummy regressors in quantile regression.<sup>4</sup>

Therefore, in order to keep consistency with the documented log-linearity of wages and education we shall assume that  $\phi_{ss} = 0$  so that the return to education  $(\beta_0 + \phi_s)$  is independent of education. Note that although the presence of  $\phi$  introduces a potential non-linearity in the above log-linear Mincer equation, equation (6) is not necessarily inconsistent with a linear relationship between log wages and education because of the positive correlation between  $\beta_{ij}$  and education.

For instance, as pointed out by Card (1995a), if for a given level of ability, wages are a concave function of education, the data for the population as a whole could still trace out a convex relationship between wages and education. He considers the case where  $\phi = b_i S_{ij} - 0.5k_1 S_{ij}^2$  with  $b_i$  reflecting variations in ability across individuals. Among individuals with the same ability, a

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<sup>4</sup> In fact, in his analysis of U.S. CPS data Park (1994) concludes that the non-linearity associated with college graduation is likely to be associated with more serious measurement error in the reports of years of education in the 14 to 16 years range. He concludes that any bias in conventional (log-linear) estimates of return to education is likely small due to the small fraction of workers falling in this range of schooling.

concave earnings-schooling relation arises since those with lower marginal costs of schooling (lower  $r_j$ ) obtain more education. Across individuals with different abilities, the earnings-schooling relation tends to be convex since the more able choose more education. The shape of the overall (mean) cross-sectional relation will depend on the balance between the relative variances of  $b_i$  and  $r_j$  in the population. We discuss the issues involved in points (ii)–(iv) below.

### 3.1. Quantile regression and unobserved heterogeneity

Unobserved ability induces heterogeneity in the distribution of earnings conditional on education through its effect on both the intercept and the education coefficient in (6). In this case the labor market cannot be well characterized by a single rate of return to education. Consider the simple linear location-scale case where  $\phi_{ij} = \delta A_j S_{ij}$  so that returns are given by:

$$\partial \ln(Y_{ij}) / \partial S_{ij} \equiv \beta_j = \beta_0 + \delta A_j \quad (7)$$

where  $(\delta)$  captures the effect of ability on the return to education. If  $\delta < 0$ , returns decrease with ability so that education compensates for family genetic differences. The converse is true for positive  $(\delta)$ .

This yields a conventional random coefficients model that is central to the recent literature. Let  $Z = (F, X)$  and suppose  $(S_{ij})$  can be treated as exogenous. Then OLS on (6) consistently estimates  $\partial E(\ln(Y_{ij}) | (Z_{ij}, S_{ij})) / \partial S_{ij} = \beta_0 + \delta \bar{A}$ : the return to education for an individual with *mean* ability or the “average treatment” effect of schooling on wages. Ashenfelter and Rouse (1998) estimate  $(\delta)$  explicitly by including an interaction term between education and the average education of a pair of twins as a regressor in (6). Heteroscedasticity in earnings disturbances can be readily addressed using standard econometric methods.

The drawback of this approach is that estimates of the  $(\beta_{j,s})$  rely on restrictive parameterizations of the interaction between education and unobserved ability. In particular, the random coefficients model in (7) implies that  $(\beta_j)$  either decreases or increases monotonically with ability. Moreover, it proves difficult in practice to separately identify the effect of ability on  $\beta_j$  as reflected in imprecise estimates of the interaction coefficient.

Regression quantiles provide a more flexible approach to characterizing the effect of education on different percentiles of the conditional wage distribution. With exogenous  $S_{ij}$ , a zero conditional quantile restriction on the error  $v_{ij}$  implies that the effect of education on the  $\tau$ -th quantile of  $Y_{ij}$  conditional on the observables in (6) is:

$$\frac{\partial Q_\tau(Y_{ij} | Z_{ij}, S_{ij})}{\partial S_{ij}} \equiv \beta_\tau = \beta_0 + \frac{\partial Q_\tau(\phi(S_{ij}, v_{ij}) | Z_{ij}, S_{ij})}{\partial S_{ij}} = \beta_0 + G_v^{-1}(\tau | Z_{ij}, S_{ij}) \quad (8)$$

where  $G_v$  is some transformation of the distribution of abilities in the population. This follows from our assumption that the marginal benefit of education is independent of the level of education and noting that  $\ln Q_\tau(Y) =$

$Q_\tau(\ln(Y))$  because of the equivariance of quantiles to monotonic transformations.

Here  $\beta(\tau)$  in (8) can be regarded as a measure of the “quantile treatment” effect of education on wages for a given  $\tau$  in  $(0,1)$ . Quantile regressions for different values of  $\tau$  yield estimates of the whole family of returns to education reflecting the distribution of abilities across individuals. The interaction between education and ability can then be explored by comparing  $\beta(\tau)$  at different quantiles  $\tau_k$  and  $\tau_s$ , for  $s \neq k$ . In the special case of equation (7) above, equation (8) reduces to  $\partial Q_\tau((Y_{ij}|Z_{ij}, S_{ij}))/\partial S_{ij} = \beta_0 + \delta Q_\tau(A_j)$  so that simple comparisons of the  $\beta(\tau)$  reveal the sign of  $\delta$ . A robust test of the hypothesis of heterogeneity ( $\beta_\tau \neq \beta$  for some  $\tau$ ) can be based on a test of whether the estimated return coefficients differ across quantiles (Koenker and Bassett, 1982). Unlike prior approaches, this does not impose strong parametric restrictions on the type of interaction between ability and education such as monotonicity, thus allowing to go beyond the convenient but more simplistic random coefficients model implied by (6)–(7).

As indicated previously, recent findings of heterogeneous returns based on estimation of quantile wage equations come close to such a characterization such as Buchinsky (1994) for the U.S., Mwabu and Schultz (1996) for South Africa, Fitzenberger and Kurz (1998) for Germany, and Machado and Mata (2000) for Portugal. However, this work does not focus on addressing the potential biases arising from endogeneity and measurement error in education, and does not structurally model the source of heterogeneity. Since  $Q_\tau(v_{ij}|S_{ij}) \neq 0$  because of (2), quantile regressions on a Mincer equation like (6) yield inconsistent estimates of the family of quantile returns to education just as OLS delivers an inconsistent estimate of the mean return. In fact, varying returns to education can be a result of an endogeneity bias that varies across quantiles rather than evidence of actual ability-based differences in the market premiums to education. The data on twins allow us to address both simultaneity and measurement error so as to more carefully uncover the evidence for “true” heterogeneity in the returns to schooling.

### 3.2. The endogeneity of schooling

In our model, individuals from higher ability families acquire more education due to lower implicit costs of schooling and/or higher returns to education. Most previous twin studies on returns to education have addressed this endogeneity of schooling in two ways. One approach (Ashenfelter and Krueger, 1994 and Ashenfelter and Rouse, 1998) treats  $A_j$  as an unobserved family effect and estimates a “fixed effects model” based on the Mincer differenced equation corresponding to (6) for each twin pair. Since (3) and (6) imply that  $E(\Delta \varepsilon_{ij} | \Delta S_{ij}, \Delta X_{ij}) = 0$  where  $\Delta$  is the difference operator, OLS on differenced data consistently estimates the average return to education.

One might naively consider quantile regression on a differenced Mincer equation since then  $Q_\tau(\Delta \varepsilon_{ij} | \Delta S_{ij}) = 0$ . However, this has a fundamental drawback. Unlike least squares, differencing in the quantile regression context is not equivalent to a fixed effects estimator. Quantiles of the sum of two random variables are not equal to the sum of the quantiles of each random variable. When differencing in quantile regression, the order of the individuals matters. Specifically, quantile estimates of education coefficients from a differ-

enced equation would reflect the effect of additional education on the quantiles of the conditional distribution of within-twins wage differentials, rather than the outcome of interest: the change induced by education in the quantiles of the conditional wage distribution. Thus, it is not possible to recover the quantile estimates obtained using data on levels from the estimates of quantile regressions on differenced data. Moreover, the natural attempt to estimate the fixed effects model including family specific dummies is also futile given the unavoidable ambiguity in the identification of the quantile fixed effects with only two observations per family.

An alternative approach is to parameterize and estimate the omitted ability variable bias by explicitly including a proxy for family ability in the set of regressors in equation (6).<sup>5</sup> Provided that the proxy accounts for any “family effects” on the absolute level of earnings and education, this approach also yields consistent estimates of the returns to education. Based on the model in section 2, we could use the education of a twin’s sibling, the average twins’ education, or father’s education as proxies. The quantile coefficients on these variables yield alternative estimates of the ability bias in estimates of returns to schooling that ignore schooling endogeneity. This is the approach we use in our empirical work and we label the resulting specifications as “family effects” models.

### 3.3. Measurement error in education

Measurement error in reported schooling can arise because of the recall errors common in survey data. This is particularly important since it is well known that controlling for absolute ability bias using family education variables as proxies exacerbates existing measurement error biases (Griliches, 1977). The available twins data provides an interesting way to address this problem.

As reported in Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998), twins are asked to report on the education level of their sibling and of their parents. Letting  $(S_{nj}^k)$  be twin  $k$ ’s report of the  $n$ -th family member, we can expect such cross-reports to satisfy (3) so that:

$$S_{nj}^k = S_{nj}^* + u_{nj}^k \quad (9)$$

where  $u_{nj}^k$  denotes *iid* measurement errors over  $n$  and  $j$ . We use these cross-reports as instruments for a twin’s reports of own and other family members’ education. As in previous studies with these data, we use these multiple reports of education to estimate models that relax the classical assumption of uncorrelated measurement errors in the own-reports of a twin. This may occur if a twin that overreports (underreports) his or her own education level is also more likely to overreport (underreport) the education level of his or her sibling and of his or her parents.

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<sup>5</sup> This is in the spirit of the control function estimators proposed by Heckman and Robb (1985) for a random coefficients model of treatment effects with endogenous treatment. Conneely and Uusitalo (1998) recently employed this approach. Heckman and Vytlačil (1999) discuss related mean and scale independence conditions for identification of the mean return to schooling in this model that are weaker than the independence assumption (3). However, the latter is required here given our focus on characterizing the distribution of returns.

#### 4. 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 Current Population Survey (CPS) with some twins-specific questions added. This is the same data used by Ashenfelter and Rouse (1998), expanded 1 year and recently analyzed by Rouse (1999). As they show, the mean characteristics of the sample are quite similar to the population at large. Sample characteristics are reported in columns 1 and 2 of 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. Ashenfelter and Rouse (1998) also note these similarities and differences.

Columns 3 through 11 of Table 1 report mean regression results employing econometric specifications similar to Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998) and Rouse (1999) who focused on estimating the average 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 1 provides a summary of the data and specifications that will be extended to the quantile regression framework below.

Columns 3–7 of Table 1 estimate simple empirical Mincer wage equations. Column 3 reports the simple least squares regression of the log of earnings on age,  $(age)^2$ , a gender indicator equal to 1 if the individual is female 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 4 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 (an anomalous result also found in previous studies using these data) but is not statistically different from zero. The mean return to education estimated in column (3) is 10.8%.<sup>6</sup> As we have stated earlier and as is well documented in Griliches (1977) and Card (1999), this estimate is potentially upward biased due to unobserved ability and downward biased due to measurement error. Also, this is likely to be lower than the returns to education from the standard Mincer earnings studies since we use age rather than Mincerian potential experience. The latter would also be subject to endogeneity and measurement error biases. A great deal of effort has been focused on determining the “true” return to education after accounting for these biases. Card (1995a) provides an important and interesting summary of a set of papers that find that simple least squares estimates seem to be downward biased.<sup>7</sup>

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<sup>6</sup> A referee pointed out the issue of selection into the labor market, especially in the case of women. We were surprised to find very little work on the issue of sample selection in estimating mean returns to education (see Angrist, 1995). However, the data we use only includes twins with positive wages so we are not able to address selection in this paper. However, we briefly report quantile regression estimates of returns to education by gender (in a footnote below) as a first step toward considering the robustness of our results to selection issues.

<sup>7</sup> These studies include Angrist and Newey (1991), Angrist and Krueger (1991), Angrist and Krueger (1992), Butcher and Case (1994), Card (1995b), and Kane and Rouse (1995).

**Table 1.** Sample Statistics and Mean Estimates of the Return to Schooling

	Means			Levels Models (Columns 3–7)					Differences Models (Columns 8–11)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)		
Education	14.13 (12.04)	14	0.108 (0.009)	0.120 (0.008)	0.114 (0.009)	0.111 (0.009)	0.123 (0.009)	0.088 (0.018)	0.095 (0.017)	0.119 (0.029)	0.167 (0.043)		
Age	37.75 (11.37)	36	0.099 (0.009)	0.087 (0.019)	0.089 (0.010)	0.099 (0.009)	0.087 (0.010)	0.087 (0.010)	0.087 (0.010)	0.087 (0.010)	0.087 (0.010)		
(age) <sup>2</sup>			-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)	-0.001 (.0001)		
Female	0.58 (0.49)	1	-0.335 (0.035)	-0.266 (0.035)	-0.266 (0.035)	-0.334 (0.035)	-0.265 (0.035)	-0.265 (0.035)	-0.265 (0.035)	-0.265 (0.035)	-0.265 (0.035)		
White	0.92 (0.28)	1	-0.079 (0.063)	-0.096 (0.060)	-0.108 (0.060)	-0.078 (0.063)	-0.095 (0.060)	-0.095 (0.060)	-0.095 (0.060)	-0.095 (0.060)	-0.095 (0.060)		
Married	0.62 (0.48)	1	0.080 (0.044)	0.080 (0.044)	0.082 (0.044)	0.084 (0.044)	0.084 (0.044)	0.084 (0.044)	0.084 (0.044)	0.084 (0.044)	0.084 (0.044)		
Union	0.21 (0.41)	0	0.099 (0.042)	0.099 (0.042)	0.103 (0.042)	0.100 (0.042)	0.100 (0.042)	0.100 (0.042)	0.100 (0.042)	0.100 (0.042)	0.100 (0.042)		
Tenure	8.48 (8.82)	5	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)	0.020 (0.002)		
Father's education	12.24 (3.15)	12	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)	0.013 (0.006)		
N	858	858	858	858	858	858	858	429	429	429	149		
R <sup>2</sup>			0.339	0.395	0.397	0.397	0.397	0.052	0.128	0.128	0.128		

*Source:* Data are from Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998), and Rouse (1999).

*Notes:* (a) Wage figures are in real 1995 dollars. Standard errors are in parentheses.

(b) 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.

(c) The instrument used in cols. 6–7 is twin 1's report of twin 2's education and vice versa and in cols. 10–11 is twin 1's report of twin 2's education minus twin 2's report of twin 1's education and vice versa.

(d) Col. 11 is from Ashenfelter and Krueger (1994). Our sample size differs from Ashenfelter & Krueger (1994) as we use an extract from Rouse (1999) which includes three additional years of the Princeton Twins Data. Rouse (1999) 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 ..."

The other columns in table 1 present the results of estimating additional, yet similar, specifications that address these ability and measurement error biases. Column 5 presents the estimates for a model that tries to control for endogeneity bias using father's education as a proxy for family specific ability. We can see that this reduces the return to education from 12% (column 4) to 11.4% and that the coefficient on father's education is significant, thus consistent with an upward ability bias.

Columns 8–11 estimate models where the data are “differenced.” Each unit of observation is created by subtracting each given variable from his or her twin's. Column 8, then, is simply the regression of the difference in log twin's wages on the difference in reported education for the twins. Comparison of the OLS and IV estimates (reported in columns 9 and 10) suggest the presence of a slight downward bias in the mean return due to measurement error in education. Instrumental variables results from a specification similar to column 7 that includes father's education (not reported) are also consistent with this view.

Column 10 contains our mean estimate that is most closely related to Ashenfelter and Krueger's (1994) final estimate (re-printed as column 11). 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 education. Our resulting estimate of the return to education 11.9% is about 10% higher than the least squares estimate of 10.8% but is considerably lower than Ashenfelter and Krueger's (1994) estimate of 16.7%. Rouse (1999), using the same four years of data that we use (Ashenfelter and Krueger, 1994 use only one year), 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. We now turn attention away from estimating the mean return toward estimating and testing the implications of our simple theoretical model of heterogeneity in the returns to schooling.

## **5. Estimation details and empirical results**

The main 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. We outline in more detail the framework used to develop our empirical models and formal tests for heterogeneity in the returns to education. Section 5.1 provides some details of our estimation and testing procedures. In Sections 5.2 through 5.6 we describe the specifications and discuss the empirical results. Finally section 5.7 briefly describes the quantile estimates of other covariates in our specifications.

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 rationale behind these models roughly follow the empirical work in the recent literature on twins (Ashenfelter and Krueger, 1994, Ashenfelter and Rouse, 1998, and Rouse, 1999) replicated in Table 1.



## 5.1. Overview of econometric methods and testing

### *Quantile regression and rank tests*

In general, we will be interested in the following linear model for the  $\tau$ -th conditional quantile of  $Y$ :

$$Q_\tau = X\beta(\tau) \quad (10)$$

Estimation of the  $\beta(\tau)$  coefficients (the “regression quantiles”) is based on a sample of  $n$  observations of  $Y$  and  $p$  explanatory variables collected in the matrix  $X$ . The interesting case arises when the  $\beta(\tau)$  coefficients differ systematically across  $\tau$ 's, suggesting that the marginal effect of a particular explanatory variable is not homogeneous across different quantiles of the conditional distribution of  $Y$ . Estimation of  $\beta(\tau)$  proceeds by solving a linear program as in Koenker and Bassett (1978).

Let  $b_n = (b_n(\tau_1), \dots, b_n(\tau_m))$  be a  $pm$  vector of  $p$  estimated regression quantile coefficients for  $m$  different quantiles based on a sample of  $n$  *iid* observations; and let  $\beta$  be its population counterpart. General linear hypotheses like  $H_0: H\beta = h$  can be tested using the following Wald-type statistic:

$$T_n = (Hb_n - h)'[H(\Omega \otimes (X'X)^{-1})H']^{-1}(Hb_n - h) \quad (11)$$

which under the null hypothesis has a  $\chi^2$  distribution with  $\text{rank}(H)$  degrees of freedom and  $\Omega$  is a  $m \times m$  matrix with typical element:

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

An alternative approach can be based on rank tests, which are robust to outliers in  $Y$  and are asymptotically distribution free. Let  $X = [1 : X_A : X_B]$  and suppose we are interested in testing the linear hypothesis  $H_0: \beta_B = 0$  vs  $H_a: \beta_B \neq 0$  where  $\beta_B$  is the vector of  $q$  linear regression quantile coefficients of the  $q$  explanatory variables in  $X_B$ . The following statistic proposed by Gutenbrunner, Jureckova, Koenker and Portnoy (1993)

$$W = (Y_r'MX_B(X_B'MX_B)^{-1}X_B'MY_r)/C \quad (12)$$

has an asymptotic  $\chi^2(q)$  distribution under the null hypothesis, where  $Y_r$  is an estimated vector of ranks of the observations,  $M = I - X_A(X_A'X_A)^{-1}X_A'$ , and  $C$  is a quantity that does not depend on the distribution of the errors. The ranks vector  $Y_r$  can be obtained as a by-product of the computation of the regression quantiles for the linear model under the restricted model. We used this approach to construct confidence intervals for the quantile regression coefficients obtained in the Non-IV models. Koenker (1994) discusses computational and theoretical advantages of this approach as well as Monte carlo results in favor of rank tests.

An alternative approach is to construct estimates of the standard errors of  $b_n$  and tests of equality of quantile slope coefficients based on the *bootstrap* which has been shown to perform well in practice (Buchinsky, 1995). The reported heterogeneity test results in the paper are based on the design matrix variant of this approach. Results based on sparsity estimation were very similar. All bootstrap simulations are based on 500 repetitions.

As in the OLS case, when some of the explanatory variables are determined simultaneously with the response variable, a bias arises in quantile regression estimators due to the dependence between the regressors and the error term. Following Powell (1983), consider, in general terms, the following structural equation:

$$Y = Y_1\gamma + X_1\beta + u \quad (13)$$

where  $Y$  is the response variable,  $Y_1$  is a  $n \times g$  matrix of endogenous variables determined simultaneously with  $Y$  (like education, in our case),  $\gamma$  is the vector of associated coefficients and  $X_1$  is a  $n \times k_1$  matrix of exogenous (predetermined) regressors.

Assuming that there is a set of  $k_2$  instrumental variables collected in the matrix  $X_2$ , we will use an instrumental variables quantile regression estimator that 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  $\xi_\tau$  that solves the quantile regression problem as stated in Koenker and Bassett (1978) for the model specified in (13) 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), and Chen and Portnoy (1996), extending Corollary 3.1 in Powell (1983). To the structural equation (13) there corresponds the following reduced form equations for variables  $Y$  and  $Y_1$ :

$$Y = X\Pi_1 + V \quad (14)$$

and

$$Y_1 = X\Pi + v \quad (15)$$

where  $X = [X_1, X_2]$  is a  $n \times (k_1 + k_2)$  matrix collecting all the exogenous variables and  $V$  and  $v$  are vectors of *i.i.d.* error terms.

Under some regularity conditions, the asymptotic distribution of the two-stage quantile regression estimator, based on Chen (1988) and Chen and Portnoy (1996) and Corollary 3.1 of Powell (1983), is given by the following result (Also, see Ribeiro (1996)):

$$\sqrt{n}(\xi_\tau^* - \xi_\tau) \rightarrow N(0, CQ^{-1}) \quad (21)$$

$$C = E[f(F^{-1}(\tau))^{-1}\varphi_\tau(v_i) - V_i\gamma]^{-1} \quad (22)$$

where  $Q = \text{plim } n^{-1}(Z'Z)$  with  $Z = (X\Pi_1, X_1)$ ,  $\varphi_\tau(v_i) = \tau - I(v_i < 0)$  is the  $\tau$ -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  $n^{-1}(Z^*Z)$  with  $Z^* = (X\Pi_1^*, X_1)$  and  $\Pi_1^*$  is the OLS estimate of  $\Pi_1$  in equation (14),  $V_i$  and  $v_i$  are replaced by the residuals of the least squares fit of equations (14) and (15) respectively, with  $u_i = v_i - V_i\gamma$ , and  $\gamma$  is replaced by its (consistent) quantile regression estimate obtained from equation (13) in the second stage estimation. The expectation term is estimated by its sample analogue. This also requires the estimation of the *sparsity* function which is carried out using standard non-parametric smoothing techniques. The reported tests for heterogeneity in this context are based on the suitable variation of the  $X$ - $Y$  version of the bootstrap.

There is some potential ambiguity in the interpretation of quantile regression estimates in the context of instrumental variables estimation. We have used methods proposed by Chen (1988) and Chen and Portnoy (1996) following the earlier work of Powell (1983). Other recent empirical papers have followed a similar strategy including Levin (2000) and Ribeiro (2000). Abadie, Angrist, and Imbens (2000) offer another approach to the application of instrumental variables quantile regression.

## 5.2. 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  $\beta(\tau)$ 's for the 5th to 95th quantiles are plotted in increments of 0.05 and the figure is separated into five sub-figures according to the covariates included in the estimation. In addition to controlling for education these plots control for B) age, race, and gender, 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) ("All") controls for age, race, marital status, union, and tenure.

We focus our attention on the specification that includes all covariates (Figure 1E). The 90% confidence bounds are also reported in the figures. Recall that homogeneity in returns would imply that the figures are flat so that it is possible to draw a horizontal line within the confidence interval band. A cursory examination of the figures suggests the presence of heterogeneity in the returns to education (the confidence bands in each figure do not include  $\beta_\tau = \beta_0$  for any  $\beta_0$ ). The returns are, in general, increasing for higher quantiles of the conditional distribution of wages. However, there is a striking increase in the return from the low quantiles to the middle quantiles going from 9.2% at the 0.05 quantile to 13.1% at the median (compared to the mean return of 12% reported in column 4 of Table 1), after which the returns remain essentially constant. Note also that the magnitude and the pattern of the estimates of the returns to education remain remarkably similar across specifications (see Figure 1). Therefore, for this simple specification, the returns do not appear to be homogenous.

We test whether the observed differences are statistically significant across quantiles and report the results of such tests in Table 2, panel A. The tests confirm the visual impression. The tests of equality of returns between the low quantiles and the middle quantiles, and between the low and high quantiles reject the hypothesis of homogeneous returns at 1–2% significance levels. For example, there is a statistically significant difference between the returns at the 0.10 and 0.50 quantiles ( $p$ -value = 0.016). Note, however, that the differences

Figure 1A. Returns to Schooling: Levels, No IV  
Education Only

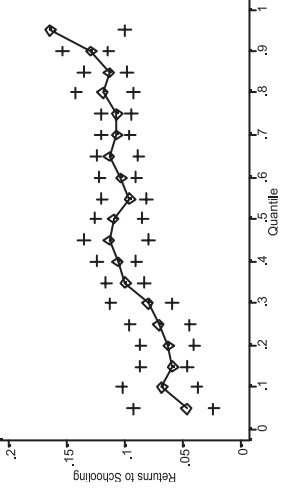


Figure 1B. Returns to Schooling: Levels, No IV  
Base Only: Age, Race, Gender

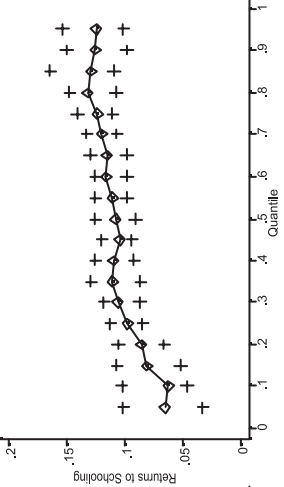


Figure 1C. Returns to Schooling: Levels, No IV  
All but Tenure: Age, Race, Gender, Married, Union

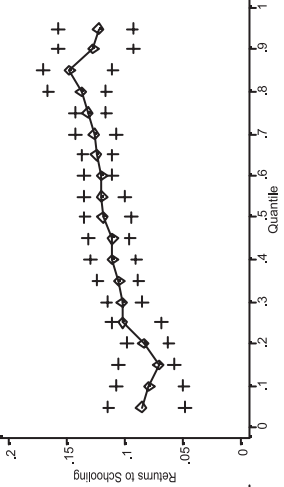


Figure 1D. Returns to Schooling: Levels, No IV  
ALL but Union: Age, Race, Gender, Married, Tenure

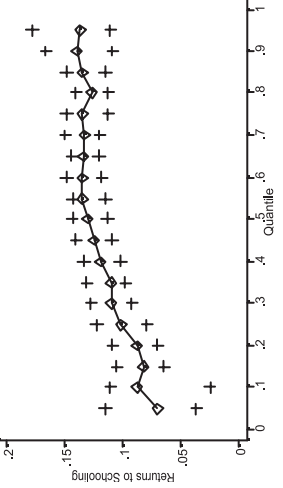
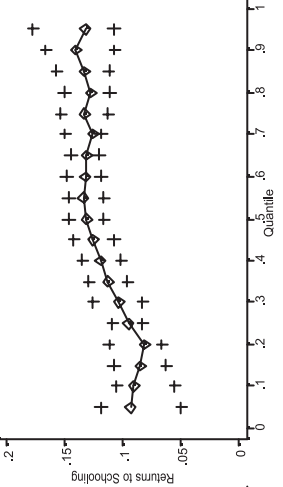


Figure 1E. Returns to Schooling: Levels, No IV  
ALL: Age, Race, Gender, Married, Union, Tenure



**Fig. 1. Returns to Schooling: Levels, No IV**  
Note: Estimation Performed in S+; see text

**Table 2.** Tests of Equality of Returns (levels models) 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		<i>p</i> -value	<i>p</i> -value
0.10	0.25	0.7793	0.9088
0.10	0.40	0.0731	0.1317
0.10	0.50	0.0158	0.1173
0.10	0.60	0.0155	0.0448
0.10	0.75	0.0204	0.0987
0.10	0.90	0.0294	0.2084
0.25	0.40	0.0109	0.0326
0.25	0.50	0.0012	0.0293
0.25	0.60	0.0010	0.0068
0.25	0.75	0.0044	0.0363
0.25	0.90	0.0215	0.1257
0.40	0.50	0.0967	0.7040
0.40	0.60	0.1451	0.2505
0.40	0.75	0.2310	0.5826
0.40	0.90	0.2565	0.8077
0.50	0.60	0.9024	0.2916
0.50	0.75	0.8426	0.7532
0.50	0.90	0.6114	0.9473
0.60	0.75	0.8840	0.6115
0.60	0.90	0.6301	0.6764
0.75	0.90	0.6564	0.8766

*Note:* This table corresponds to tests of equality of returns to schooling across quantiles for the levels (“all variables”) model with and without instrumental variables corresponding to FIGURES 1E and 2E. The other independent variables we control for are age, age<sup>2</sup>, race, gender, married, union, and tenure. *P*-values are based on the bootstrap and the percentile method.

between the middle and higher quantiles are not significant which is consistent with the flattening out of Figure 1 in the right tail. These findings are consistent with the existence of a complementary relationship between ability and education in the generation of earnings which varies for those in the lower tail of the conditional distribution of wages (i.e., the low ability) and contrasts with the constant but higher upper tail marginal returns.

### 5.3. Levels model with instrumental variables

Of course, the results above are still subject to the ability and measurement error biases described above. As a first step toward addressing these problems we estimate the levels model using instrumental variables for the education variable to alleviate measurement error. We follow the previous literature and use twins #2’s report of twin #1’s own education (and vice versa) as an instrument. These results are reported in Figure 2 which is arranged like Figure 1 in that we report results for five different sets of covariates.

The same general conclusions may be again drawn from Figure 2. Failure to address the measurement error in education in the levels model does not seem to create a significant downward bias in the estimated returns to schooling. The estimated returns range from 9.5% to 14.1% over the quantiles,

Figure 2A. Returns to Schooling: Levels, IV  
Education Only

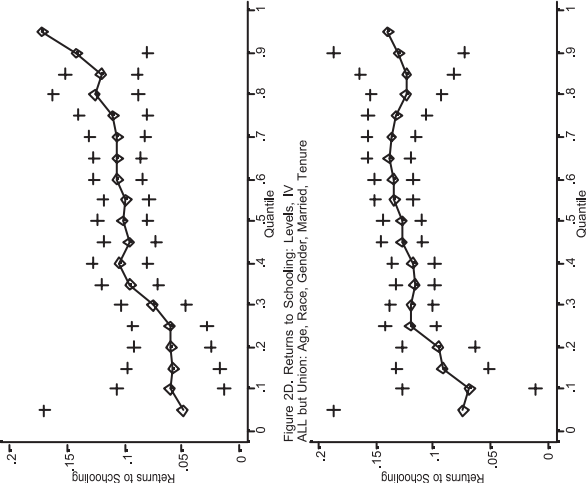


Figure 2B. Returns to Schooling: Levels, IV  
Base Only: Age, Race, Gender

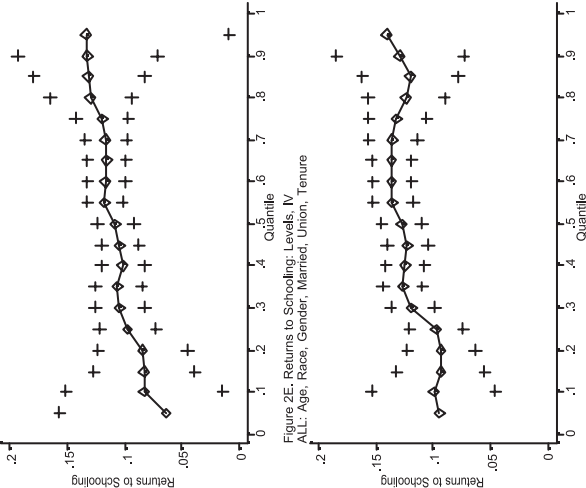


Figure 2C. Returns to Schooling: Levels, IV  
All but Tenure: Age, Race, Gender, Married, Union

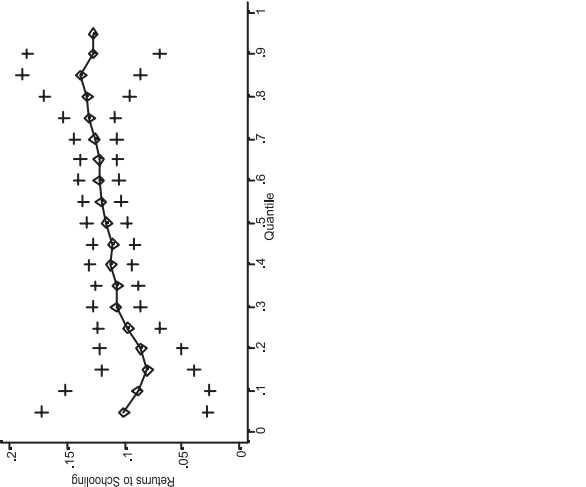


Figure 2D. Returns to Schooling: Levels, IV  
All but Union: Age, Race, Gender, Married, Tenure

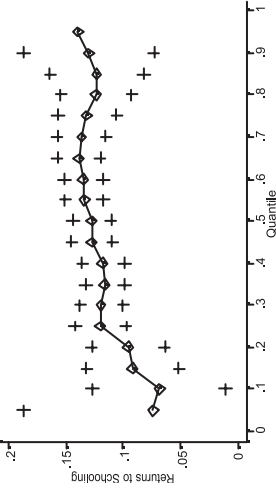


Figure 2E. Returns to Schooling: Levels, IV  
ALL: Age, Race, Gender, Married, Union, Tenure

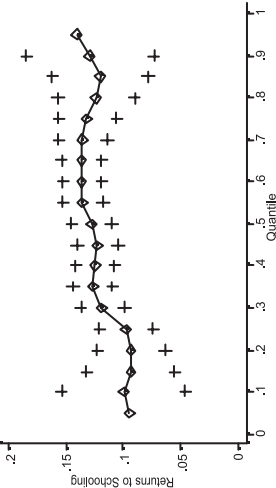


Fig. 2. Returns to Schooling: Levels, IV  
Note: Estimation Performed in S+; See Text

with a median return of 12.8%. After controlling for measurement error in the levels model, we can still see evidence of heterogeneity in returns to education with increasing returns at higher quantiles. Notice, however, that the standard error bands are somewhat wider in the instrumental variables case so that small differences are unlikely to be significant.

We report tests of significance in the levels model with instrumental variables in Table 2, panel B. The results are largely consistent with those in the levels model without instruments, supporting the visual impression of heterogeneous returns except that the tests cannot reject the hypothesis of equality of returns between extreme quantiles due to higher standard errors of these estimates. This might suggest that instrumenting affects the “true” schooling signal in own reported education more sensibly for those at the tails of the conditional wage distribution. Overall, the findings suggest that the bias that arises from measurement error in education in the levels models is not very important. In the absence of endogenous ability bias, the estimates from the previous levels models would provide relatively accurate measures of the family of returns to schooling.

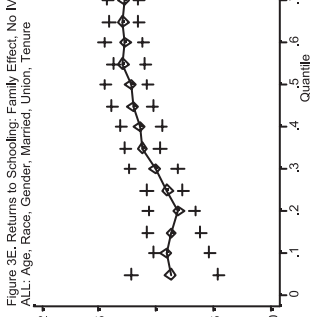
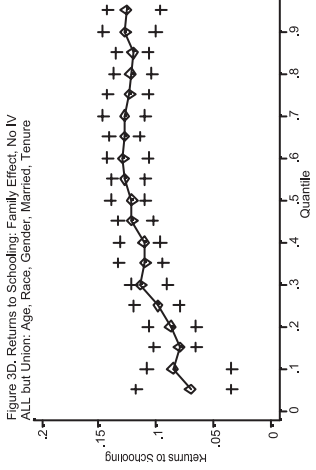
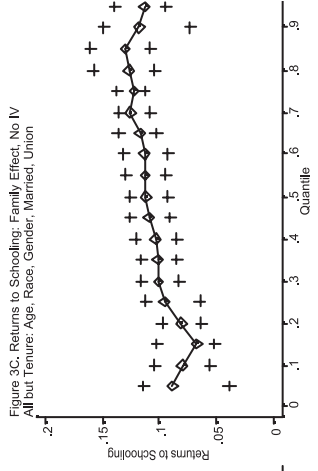
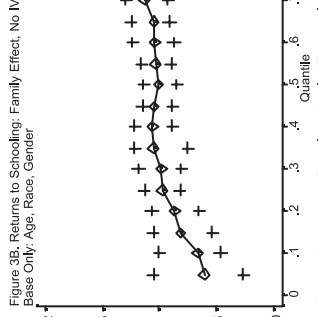
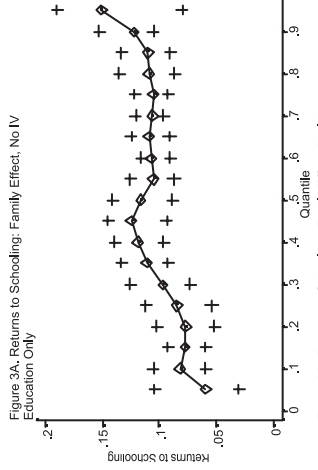
#### 5.4. Family effects model without instrumental variables

We repeat the analysis of section 5.2 while attempting to control for the well-known ability bias problem. As we stated in Section 3.2 above, the implementation of a quantile regression analogue of an OLS fixed effect or differenced model is problematic. Instead, in our quantile regression equivalent of a fixed effects model we use the father’s level of education and the sibling’s education as proxies for the family effect. We only report the results for father’s education since the results are qualitatively similar but the latter are less precise. We also estimated specifications using the average education level of the twins as a proxy for family ability. As expected, this resulted in somewhat higher estimates of the ability bias but the precision of these and the coefficients on education was much poorer. Essentially, we are redoing the analysis reported in Figures 1 and 2 with the father’s schooling level as an additional covariate. Note that even 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 lies precisely in the use of quantile regression techniques to explore this relationship based on the quantiles of wage residuals that we interpret as capturing unobservable ability to generate earnings.

Figure 3 reports the results. Clearly, including the family effects has a substantial effect on the estimated returns. In general, the curves in Figure 3 are lower than the corresponding ones in Figure 1, particularly at higher quantiles.<sup>8</sup> The returns now range from 8.8% at the 0.05 quantile to 12.2% at

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<sup>8</sup> We also investigated these specifications by gender as a potential first-step to considering selection bias into the labor force. (Recall that we only have information on wage earners so typical techniques are not possible). We find that the general patterns in returns to education across quantiles were quite similar by gender except that women’s returns seem slightly higher than men’s, especially around the 50th to 60th quantiles. We should note that even if we did find substantial differences by gender this would not be sufficient to suggest endogeneity. Nevertheless, the similarities in the patterns of heterogeneous returns by gender suggest that our results are unlikely to be driven by selection biases.



**Fig. 3.** Returns to Schooling: Family Effect, No IV  
 Note: Estimation Performed in S+; see text



the median, remaining mostly unchanged in the upper quantiles. This is consistent with our expectation that part of the return to education is absorbed by the family effect thus reflecting a positive endogeneity bias. This is seen when we plot the coefficient on father's education and sibling's education for the 19 quantiles in the appendix figure. The estimates of the endogeneity bias across different quantiles are in general increasing, though the precision of these estimates is poor. The sibling's family effects models yield a slightly higher estimate of the endogeneity bias, but the precision of the estimates is much poorer. This suggests that the findings of Buchinsky (1994) of higher returns to education at higher quantiles may 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 for those in the upper tail of the conditional wage distribution.

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. These patterns remain essentially intact when using sibling's education as a proxy for family ability. Therefore, although differences across quantiles are, no doubt, less significant, there still appears to be some heterogeneity in the returns to education. This is confirmed by the tests we report in Table 3 panel A which indicate rejection of the hypothesis of homogeneous returns when comparing the low to middle and upper quantiles. Despite the apparent substantial differences in the estimated returns between extreme quantiles, poor precision as reflected by the wider confidence bounds leads to larger  $p$ -values.

### 5.5. Family effects model with instrumental variables

As already indicated, by including measures of education to control for family effects we aggravate the potential bias arising from measurement error in schooling levels since the cross-correlation between education levels (which is 0.75 among siblings) washes away some of the "true" schooling signal in own-reported education levels. In this Section we report the results of our best attempt to control for both the ability and the measurement errors biases. This is the direct extension of section 5.3 except that we now use twin #2's report of father's education and of twin #1's own report to instrument for potential measurement error in twin #1's report of father's education and twin #1's reported education, respectively (and vice versa). In the case of sibling's education we also estimated models that allow for correlation in the measurement errors of twins' reports. Again we only report the results for the models using father's education since these results were very similar, except for the poorer precision of the estimates from the sibling's education models. We report the actual returns and confidence intervals for the IV "family effects" models in Figure 4. The returns are somewhat sporadic, increasing from 9.9% at the 5<sup>th</sup> quantile to 12.3% at the median and then declining to 10.7% at the 90<sup>th</sup> quantile. Note also that the confidence bands are wider, specially at the extreme quantiles.

A comparison with the non IV estimates of the analogous family effects 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. Considering the wider confidence bounds on

Figure 4A. Returns to Schooling: Family Effect, IV  
Education Only

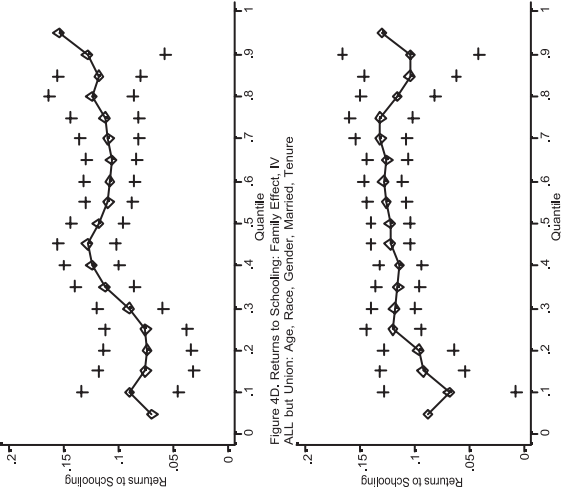


Figure 4B. Returns to Schooling: Family Effect, IV  
Base Only: Age, Race, Gender

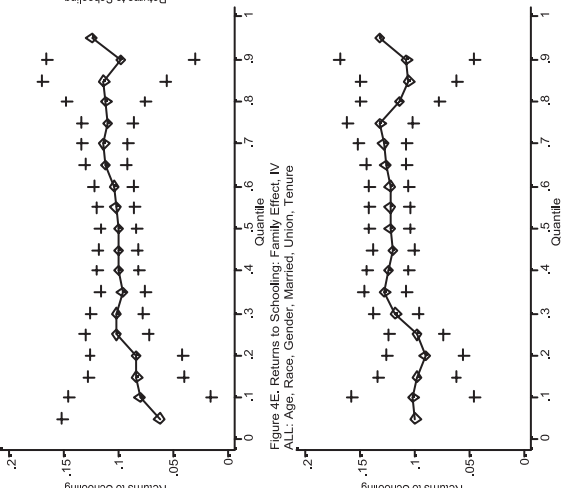


Figure 4C. Returns to Schooling: Family Effect, IV  
All but Tenure: Age, Race, Gender, Married, Union

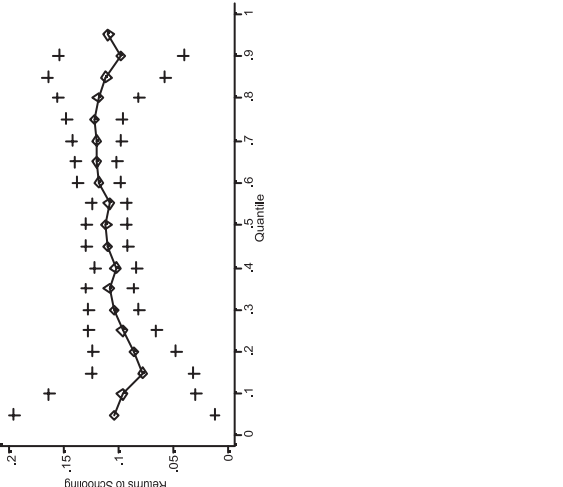


Figure 4D. Returns to Schooling: Family Effect, IV  
ALL but Union: Age, Race, Gender, Married, Tenure

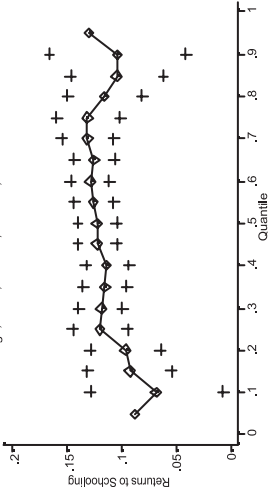


Figure 4E. Returns to Schooling: Family Effect, IV  
ALL: Age, Race, Gender, Married, Union, Tenure

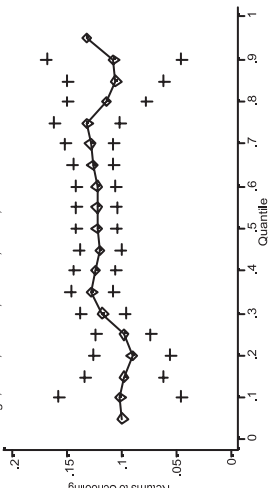


Fig. 4. Returns to Schooling: Family Effect, IV  
Note: Estimation Performed in S+, see text

**Table 3.** Tests of Equality of Returns (family effects models) 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		<i>p</i> -value	<i>p</i> -value
0.10	0.25	0.9109	0.8272
0.10	0.40	0.1366	0.1778
0.10	0.50	0.0581	0.2069
0.10	0.60	0.0349	0.2242
0.10	0.75	0.0416	0.1269
0.10	0.90	0.1144	0.8003
0.25	0.40	0.0074	0.0456
0.25	0.50	0.0036	0.0884
0.25	0.60	0.0023	0.1070
0.25	0.75	0.0064	0.0595
0.25	0.90	0.0575	0.6708
0.40	0.50	0.2907	0.9019
0.40	0.60	0.1692	0.9210
0.40	0.75	0.2710	0.5891
0.40	0.90	0.5071	0.3628
0.50	0.60	0.5119	0.9983
0.50	0.75	0.6237	0.4829
0.50	0.90	0.7995	0.3859
0.60	0.75	0.9565	0.4249
0.60	0.90	0.9743	0.3575
0.75	0.90	0.9443	0.1192

*Note:* This table presents tests of equality of returns to schooling across quantiles for the family effects (“all variables”) model with and without instrumental variables corresponding to FIGURES 3E and 4E. The other independent variables we control for are age, age<sup>2</sup>, race, gender, married, union, and tenure. *P*-values are based on the bootstrap and the percentile method.

the IV estimates these differences are likely insignificant. Figure 4E still suggests some mild heterogeneity in the returns to education, the estimated returns are higher in the middle quantiles and similar at the tails. The estimates are also less precise at the tails. Indeed, when we test for differences across quantiles (Table 3, panel B), only in comparisons between the 25<sup>th</sup> quantile and the middle quantiles do we find some evidence of heterogeneity in the returns (*p*-values between 5–10%). The estimates of the family effects based on both father’s education and sibling’s education are also more imprecise in the instrumental variable models (see appendix figure). Once again it appears that the attempts to deal with both the endogeneity bias and measurement error washes away most of the “true” schooling signal of own reported education at the tails of the conditional wage distribution leading to less precise estimates.

### 5.6. Do the endogeneity and measurement error biases matter? Are returns heterogeneous?

We now briefly summarize what we have learned from our empirical models that attempt to document the existence of heterogeneity in the returns to schooling while dealing with the two well known sources of biases. The results are summarized in Figure 5 which decomposes the differences in the estimated

Figure 5A. Levels non-IV (Figure 1E) - Levels IV (Figure 2E)

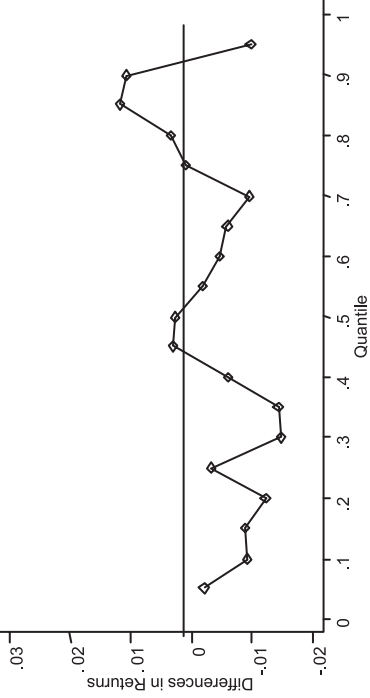


Figure 5B. Levels IV (Figure 2E) - Family IV (Figure 4E)

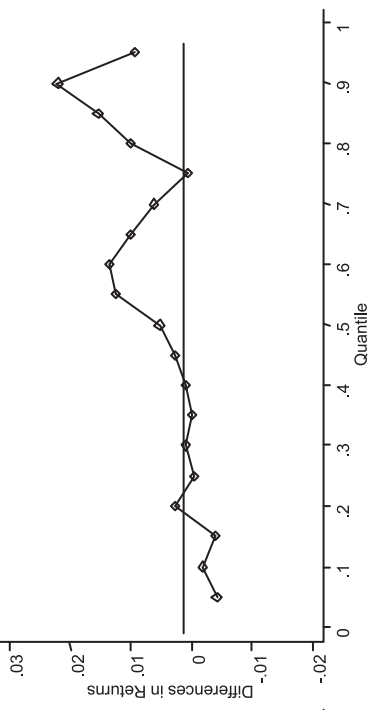


Figure 5C. Family non-IV (Figure 3E) - Family IV (Figure 4E)

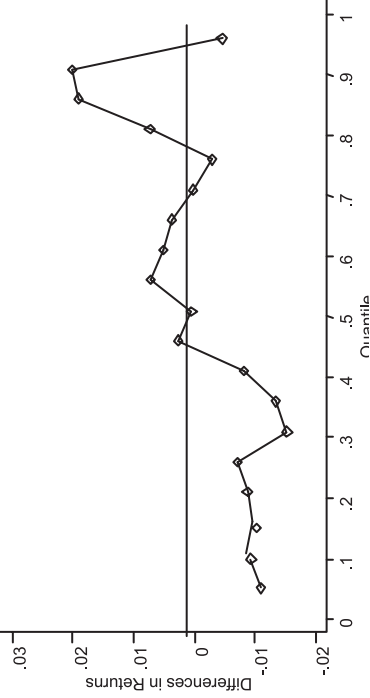
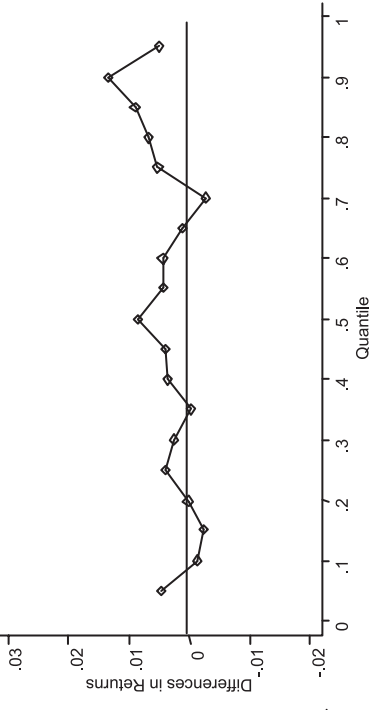


Figure 5D. Levels non-IV (Figure 1E) - Family non-IV (Figure 3E)



**Fig. 5.** Differences in Returns to Schooling by Empirical Model  
Note: Estimation Performed in S+; see text

returns to education obtained from the “all” covariates specification across our four empirical models into the endogeneity bias and measurement error components. Remarkably, the conclusions here actually hold for the four other covariate designs we use in the paper. These results also hold for the family effects models that are based on sibling’s education.

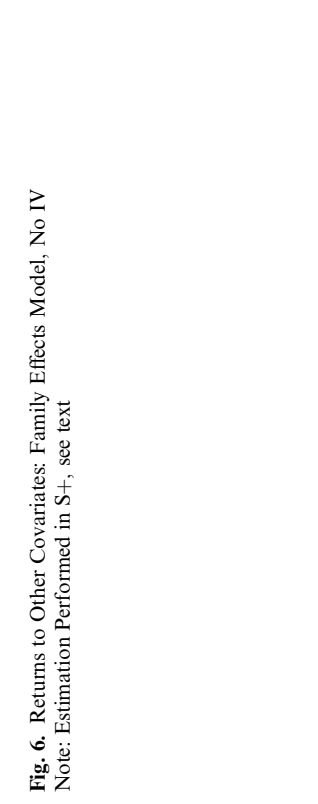
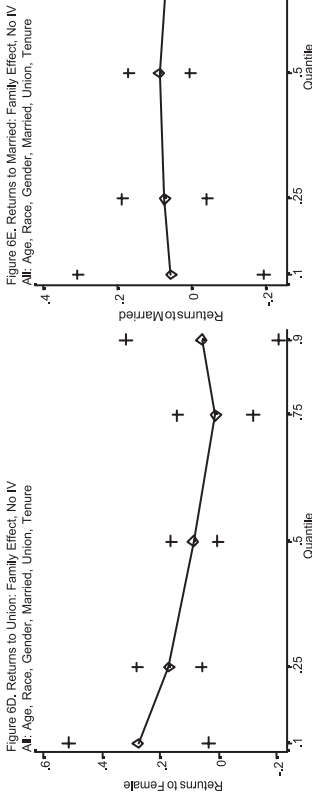
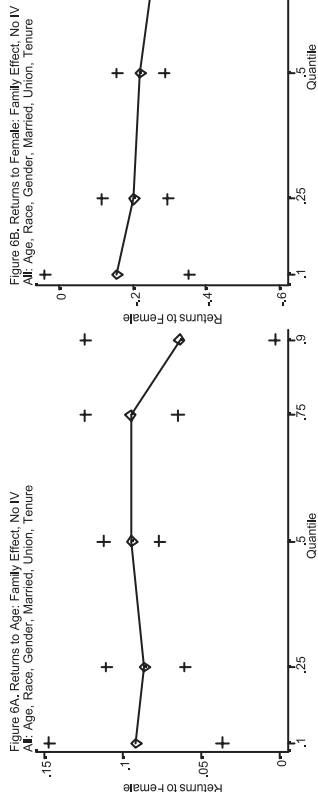
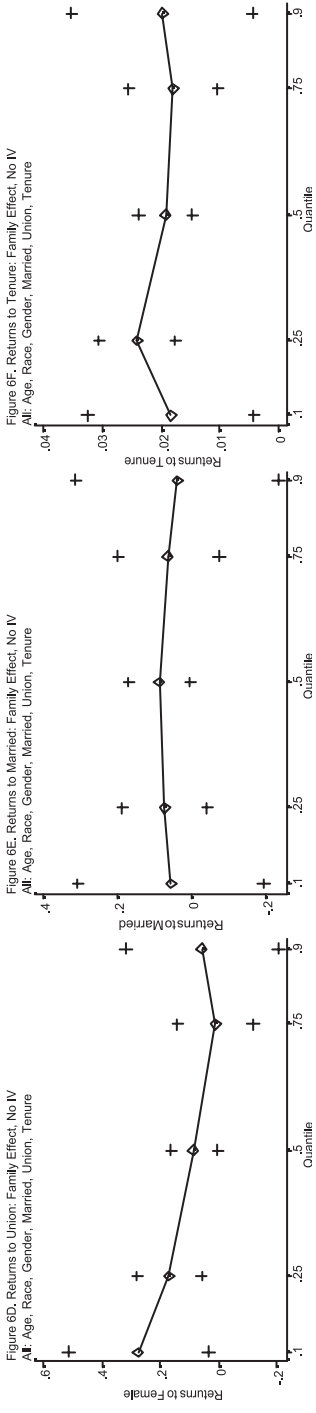
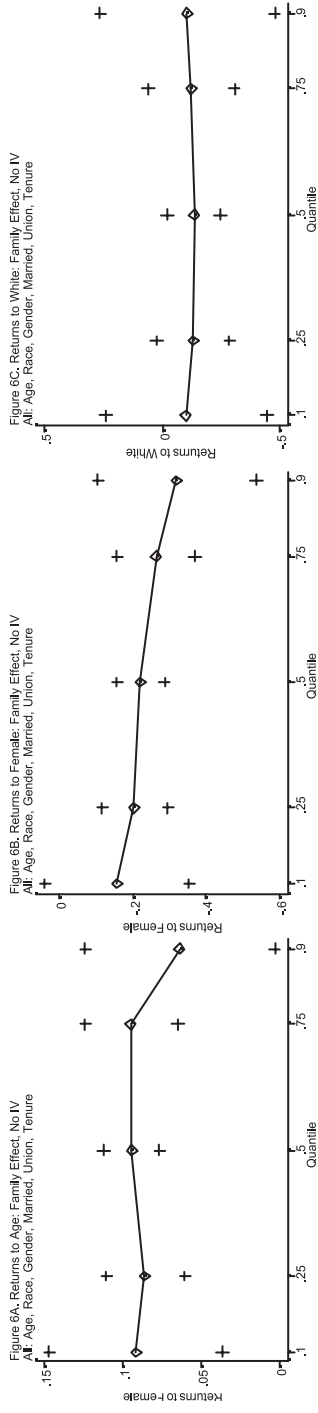
Does measurement error matter? Comparison of the levels model non-IV vs. IV (see Figure 5A) and father’s education model non-IV vs. IV (see Figure 5C) both reveal that the IV estimates seem to be slightly higher than the non-IV case in the left tail, consistent with a slight downward bias due to measurement error. This effect is more evident in the family effects models so that, as expected, in addressing schooling endogeneity any measurement error downward bias is amplified. The IV estimates actually appear to be lower than the non-IV at the high quantiles (0.8–0.9) but this probably reflects the effect of noisier estimates at the tails. So, based on this evidence we conclude that failure to account for measurement error seems to create slight downward biases in the estimates of the returns to schooling only at the lower quantiles, which are stronger in models that control for family effects in school attainment. But again, the IV estimates in family effects models are less precise, particularly at the tails.

Does ability bias matter? Comparison of estimates from the levels models non-IV vs. father’s educ models non-IV (Figure 5D) and levels models IV vs. father’s educ models IV (Figure 5B) are revealing. First, the shapes of the quantile curves of return coefficients are rather similar with an almost perfect overlap of the curves in the bottom quantiles (Figures 5B and 5D align at the zero horizontal line). Beyond the 0.40th quantile, the family models’ return curves are slightly above, so there is evidence of a slight upward ability bias in the right tail in models that do not account for endogeneity of schooling choices.

More important for the key question addressed in this paper is the fact that the pattern of return estimates remains essentially similar in both the levels and family effects non-IV models and to a lesser extent in the IV family effects models. There is a tendency for returns to increase monotonically along the bottom tail of the conditional wage distribution, returns then flatten out but tend to remain higher in the upper tail. These findings are supported by our formal tests and are inconsistent with the strictly monotonic pattern of quantile returns implied by the conventional random coefficients model that has been a focus of the recent literature. The 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 from a complementary relationship between education and ability which gives an advantage to those at the top of the conditional wage distribution but also enhances earnings potential for low-wage individuals.

## 5.7. Estimation results for other covariates

We finally briefly describe the return to the other covariates included in our empirical model. Figure 6 is a concise summary of the results from the “all” specification, which includes age, race, gender, married, union, and tenure, along with the associated 90% confidence intervals for the family effects



**Fig. 6.** Returns to Other Covariates: Family Effects Model, No IV  
Note: Estimation Performed in S+, see text

without IV models based on the sparsity method. Inference conclusions are essentially unchanged if we use bootstrap confidence intervals. Note the anomalous negative effect of race of white 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. The effect of marital status on earnings is positive but it is only significant at the median.

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) (also see Amidon, 1997). 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 (also see Chamberlain, 1994). 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 (DiNardo and Lemieux, 1996, DiNardo, Fortin and Lemieux, 1996).

## 6. Concluding comments

In this paper we present estimates of a simple model of earnings and schooling choices in which we explore the relationship between education and ability in the generation of human capital without imposing a stringent parametric structure on this relationship. We use instrumental variables quantile regression and data on identical twins to isolate the causal link between education and earnings at different quantiles of the conditional distribution of wages, while dealing with 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.

The results suggest the existence of an important upward ability bias at the high quantiles in the estimates of the returns to education that do 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 induces slight downward biases in the estimated returns to education in the low quantiles that are intensified by attempts to deal with the ability bias.

More importantly, the results provide novel evidence of the existence of two sources of heterogeneity in the returns to education. First, there is some evidence of a differential heterogeneity effect by which more able individuals become more educated. The resulting endogeneity bias increases monotonically across quantiles and thus leads to apparently higher returns to education at the high quantiles in models that do not account for the endogeneity of schooling. Therefore, the earlier estimates of heterogeneous returns to schooling from quantile wage regressions that do not control for unobserved ability (e.g., Buchinsky (1994),) may be confounding this differential endogeneity bias with any actual difference in the marginal returns to education across quantiles.

Second, once this endogeneity bias is accounted for, our results provide some evidence that there is indeed 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 unobservable abilities in the generation of earnings. In particular, the evidence supports the existence of a complementary relationship between ability and education which gives an advantage to those at the top of the conditional wage distribution but also enhances earnings potential for low-wage individuals. That is, high-ability individuals tend to have higher returns to schooling. The results thus suggest that more able individuals may attain more schooling because of lower marginal costs and/or higher marginal benefits to each additional year of education. This is consistent with the existence of a negative correlation between the marginal costs and the marginal returns to schooling along the distribution of abilities. However, the strictly non-monotonic pattern of quantile return coefficients does not conform well to a conventional random coefficients model of earnings equations. Moreover, the evidence for heterogeneity is weakened once measurement error in education is taken into account due to noisier estimates.

Our findings are at odds with the findings of Ashenfelter and Rouse (1998) of lower marginal (average) returns for higher ability individuals after controlling for the endogeneity and measurement error in schooling. However, they are consistent with the findings of higher returns for the more able of Conneely and Uusitalo (1998) based on estimation of conditional mean wage functions and the use of test scores to proxy ability.

Our results thus reassure us 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). The results are also relevant to the recent work on the role of education in increasing wage inequality (e.g., Fitzenberger and Kurz, 1998 and Machado and Mata, 2000).

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 intend 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 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, particularly exploring extensions of quantile regression methods to the analysis of panel data.

In a recent paper, Bound and Solon (1998) criticized the estimates of returns to education based on twins data questioning the assumption of independence between the optimal education choice and earnings disturbances. As they rightly argued, the validity of twins based estimates relies crucially on this assumption. In our final approach, the resulting estimated returns are never lower than 9 percent and can be as high as 13 percent at the top of the conditional distribution of wages although these differences in returns become



imprecise. If schooling and the individual component of the error term in the wage equation are positively correlated, our range of estimates can be thought to provide upper bounds on the causal effect of education on earnings.

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 may be 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 who face higher costs. On the other hand, the indication that apart from this differential ability bias, the returns to schooling are higher for those at the top of the conditional wage distribution suggests a limit on the extent to which schooling can compensate for differences in individual ability endowments. 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 may depend on the initial distribution of abilities in the generation of earnings across the population. This may include factors such as early learning environments, schooling quality and family connections that are amenable to policy changes.

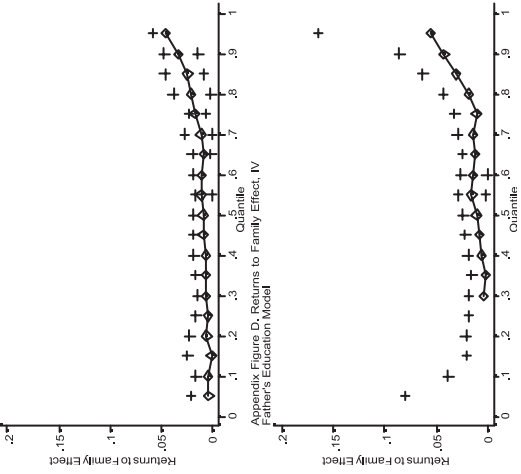
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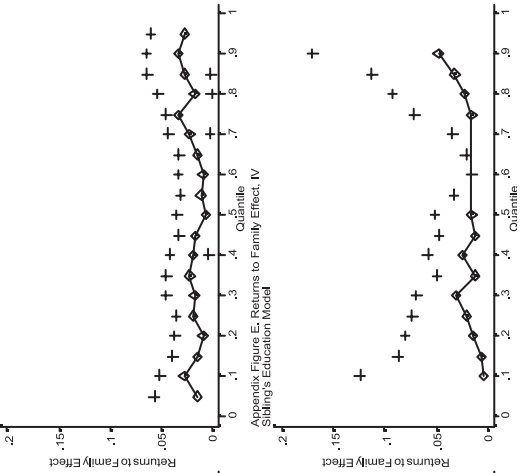
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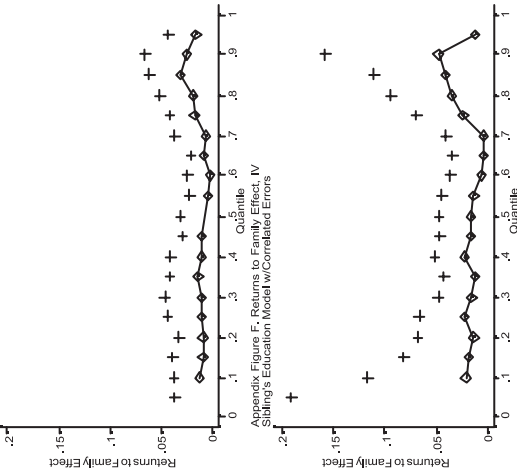
Appendix Figure A. Returns to Family Effect, No IV  
Father's Education Model



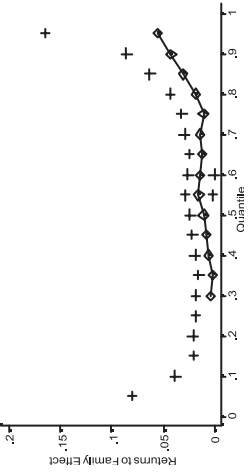
Appendix Figure B. Returns to Family Effect, No IV  
Sibling's Education Model



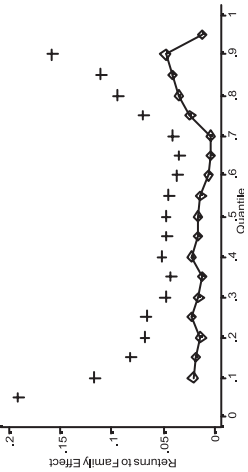
Appendix Figure C. Returns to Family Effect, No IV  
Sibling's Education Model w/Correlated Errors



Appendix Figure D. Returns to Family Effect, IV  
Father's Education Model



Appendix Figure E. Returns to Family Effect, IV  
Sibling's Education Model



**Appendix Figure. Returns to Family Effects**  
Note: Estimation Performed in S+, see text