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ABSTRACT

In this paper we use data on brothers, and fathers and sons, to estimate the economic returns to schooling. Our goal is to determine whether the correlation between earnings and schooling is due, in part, to the correlation between family backgrounds and schooling. The basic idea is to contrast the differences between the schooling of brothers, and fathers and sons, with the differences in their respective earnings. Since individuals linked by family affiliation are more likely to have similar innate ability and family backgrounds than randomly selected individuals our procedure provides a straightforward control for unobserved family attributes.

Our empirical results indicate that in the sample of brothers the ordinary least squares estimates of the return to schooling may be biased upward by some 25% by the omission of family background factors. Adjustments for measurement error, however, imply that the intrafamily estimate of the returns to schooling is biased downward by about 25% also, so that the ordinary least squares estimate suffers from very little overall bias. Using data on fathers and sons introduces some ambiguity into these findings, as commonly used specification tests reject our simplest models of the role of family background in the determination of earnings.

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In this paper we use data on brothers, and fathers and sons, to estimate the economic returns to schooling. The basic idea is to contrast the differences between the schooling of brothers, and fathers and sons, with the differences in their respective earnings. Since individuals linked by family affiliation are more likely to have similar innate ability and family backgrounds than randomly selected individuals our procedure provides a straightforward control for unobserved family attributes. Our goal is to determine whether the correlation between earnings and schooling is due, in part, to the correlation between family backgrounds and schooling. Since intrafamily estimates of the return to schooling may be biased downward by measurement error in schooling (see Griliches 1979) we also explicitly examine the sensitivity of the results to the presence of measurement error.

Our empirical results indicate that in the sample of brothers the ordinary least squares estimates of the return to schooling may be biased upward by some 25% by the omission of family background factors. Adjustments for measurement error, however, imply that the intrafamily estimate of the returns to schooling is biased downward by about 25% also, so that the ordinary least squares estimate suffers from very little overall bias. For contrasts between fathers and sons the empirical results are more complex, as specification tests indicate that simple models of the omitted family background factors are rejected by the data. Estimated returns to schooling for fathers may be biased upward by the omission of family background factors by about 30%, but adjustments for measurement error are of a similar magnitude, so that the ordinary least squares estimate suffers from little overall bias. Estimated returns to schooling for sons, however, are dramatically reduced when family background characteristics are controlled.

I. Empirical Framework

A. Basic Specification

Our analysis begins with the standard relationship (see Mincer 1974) between the logarithm of hourly wages (Y) and observed schooling (X):

$$(1) \qquad Y_{1j} = \beta_1 X_{1j} + \varepsilon_{1j}$$

$$(2) \qquad Y_{2j} = \beta_2 X_{2j} + \varepsilon_{2j}$$

where Y_{ij} and X_{ij} represent the log wage and schooling of the ith brother in the jth family. (In father-son contrasts we write Y_{ij} and X_{ij} for the log wage and schooling of the ith son (or father) in the jth family.)

The error term ε_{ij} in each equation is composed of a person-specific component, v_{ij}, and a family specific component, F_j. The family specific effect captures unchanging characteristics that are common to all family members. Thus, F varies across families but is the same for all individuals within a family. Specifically, we assume:

(3) $$Y_{1j} = \beta_1 X_{1j} + F_j + v_{1j}$$

(4) $$Y_{2j} = \beta_2 X_{2j} + F_j + v_{2j}$$

To model the potential correlation between the family effect F and the explanatory variables X we assume that (see Chamberlain 1982):

(5) $$F_j = \lambda_1 X_{1j} + \lambda_2 X_{2j} + \xi_j$$

The residual term ξ_j is assumed to be uncorrelated with the explanatory variables and the λ's are parameters. Substituting equation (5) into equations (3) and (4) yields the following reduced form equations:

(6) $$Y_{1j} = (\beta_1 + \lambda_1)X_{1j} + \lambda_2 X_{2j} + w_{1j} = \Pi_{11} X_{1j} + \Pi_{12} X_{2j} + w_{1j}$$

(7) $$Y_{2j} = \lambda_1 X_{1j} + (\beta_2 + \lambda_2)X_{2j} + w_{2j} = \Pi_{21} X_{1j} + \Pi_{22} X_{2j} + w_{2j}$$

where:

$\Pi_{11} = \beta_1 + \lambda_1$
$\Pi_{12} = \lambda_2$
$\Pi_{21} = \lambda_1$ and
$\Pi_{22} = \beta_2 + \lambda_2$

In this model the schooling of each family member enters into both family member's reduced form equations. The magnitude of the λ parameters (the coefficient of the 'siblings' schooling) measures the extent to which estimated returns to schooling are biased due to the omission of family background factors.

Least Squares provides a simple and efficient estimator of the reduced form equations (6) and (7). As specified, this model is exactly identified and has four structural parameters. Assuming, for example, that the returns to education are the same for both family members ($\beta_1=\beta_2$) makes this model over-identified. In this case, there would be 4 reduced form coefficients with which to identify the 3 structural parameters. There is a straightforward relationship between the estimates of this model with correlated random effects and the conventional "fixed effects" estimator. For the exactly identified case, the implied structural coefficients found by differencing the estimated reduced form coefficients, Π_{11}- Π_{21} and Π_{22}- Π_{12} will be numerically identical to the fixed effects estimates found by estimating the difference between equations (6) and (7):

$$(8)\quad Y_{2j} - Y_{1j} = (\Pi_{21} - \Pi_{11})X_{1j} + (\Pi_{22} - \Pi_{12})X_{2j} + u = \Delta_1 X_{1j} + \Delta_2 X_{2j} + u$$

That is, $\hat{\Delta}_1 = \hat{\Pi}_{21} - \hat{\Pi}_{11}$ and $\hat{\Delta}_2 = \hat{\Pi}_{22} - \hat{\Pi}_{12}$. Thus, the (unrestricted) reduced form estimates for the correlated random effects model will always allow the estimation of the fixed effects model. This suggests that there is never any harm in fitting the correlated random effects model when it is not over-identified, and indeed, the correlated random effects formulation has the benefit of allowing an interpretation of any bias in the OLS estimates that results from ignoring the family effect. For example, estimates of λ_1 and λ_2, should be positive if more "able" families obtain more schooling. Since the more general model with different β's (returns to education) is identified, the restriction implied by the commonly estimated fixed effects model ($\beta_1 = \beta_2$ or equivalently $-\Delta_1 = \Delta_2$) is testable. The fixed effects estimator can, therefore, be regarded as nested within the (unrestricted) correlated random effects model.

Other overidentifying restrictions, such as $\lambda_1 = \lambda_2$ may also be tested. This restriction implies that the sum of the explanatory variables $X_{1j}+X_{2j}$ provides an adequate parameterization of the family effect.

B. Correlated Random Effects with Measurement Error

The correlated random effects model may be easily expanded to allow for the possibility of measurement error in observed schooling. Suppose that both X_1 and X_2 are measured with error so that:

(9) $$X_1 = X^*_1 + m_1$$

(10) $$X_2 = X^*_2 + m_2$$

where X_1^* and X_2^* are the true level of the explanatory variables and m_1 and m_2 are measurement error terms that are mutually uncorrelated and uncorrelated with the true values of the explanatory variables. Given these assumptions, ordinary least squares estimates of equations (6) and (7) would yield inconsistent estimates with[2]:

$$\text{(11)} \quad \text{plim } \hat{\Pi}_{11} = \Pi_{11} - \frac{\Pi_{11}\psi_1 - \rho\Pi_{12}\psi_2}{1-\rho^2}$$

$$\text{(12)} \quad \text{plim } \hat{\Pi}_{12} = \Pi_{12} - \frac{\Pi_{12}\psi_2 - \rho\Pi_{11}\psi_1}{1-\rho^2}$$

$$\text{(13)} \quad \text{plim } \hat{\Pi}_{21} = \Pi_{21} - \frac{\Pi_{21}\psi_1 - \rho\Pi_{22}\psi_2}{1-\rho^2}$$

$$\text{(14)} \quad \text{plim } \hat{\Pi}_{22} = \Pi_{22} - \frac{\Pi_{22}\psi_2 - \rho\Pi_{21}\psi_1}{1-\rho^2}$$

where $\psi_1 = \dfrac{\text{var}(m_1)}{\text{var}(X_1)}$ and $\psi_2 = \dfrac{\text{var}(m_2)}{\text{var}(X_2)}$ are the noise to total variance ratio for X_1 and X_2 respectively, and ρ is the correlation between the observed X_1 and X_2.[3] Bielby, Hauser, and Featherman (1977), using repeated measures on schooling, report estimates ψ of .199, .162, and .079 using various measures.

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[2] See Maddala (1992) for a derivation of this result.

[3] Notice for $\rho=0$ these expressions reduce to the standard bias formula when only one explanatory variable is measured with error.

Siegel and Hodge (1968) report an estimate of .0668. Ashenfelter and Krueger (1992) report an estimate of ψ=.098. Illustrative calculations with formulas (11)-(14) indicate that even small amounts of measurement error may lead to considerable biases in the estimated returns to schooling in the model if the correlation ρ in sibling schooling is large. If we substitute $\text{plim}\,\hat{\Pi}_{ij}$ from (11)-(14) for Π_{ij} in (6) and (7) we obtain the population regression equations (15) and (16) in Table 1. With known values for ρ and $\Psi_1 = \Psi_2$ equations (15) and (16) are linear in the parameters and may be estimated jointly using a Seemingly Unrelated Regression (SURE) (Zellner (1962)) estimator on the sibling or father/son data.

II. The Data

The data used in this study are from the National Longitudinal Survey (NLS). The NLS was initiated in 1966 and was comprised of four groups; each with approximately five thousand respondents.[4] Several households in the survey yielded more than one respondent. Given household and relationship identifiers, it is possible to match related pairs of individuals. We were able to match 332 father-son pairs and 143 brother pairs for this study. The data used for the sons and brothers is extracted from the 1981 cross-section of the NLS. The data used for the

[4] The original cohorts used in this study were: Men aged 45-59 and Young Men aged 14-24 in 1966.

fathers is extracted from the 1966 cross-section. These dates are selected to capture the brothers at their oldest observation date and to minimize the difference between the age of the fathers and sons. For families yielding more than one father-son or brother match, the eldest son or brother is retained. This preserves independence across observations and attempts to reduce the potential lifecycle bias by retaining the son/brother farthest out on his earnings lifecycle. The analysis uses measures on log hourly wages (in cents), age, and years of schooling. Wage rates are converted into 1981 dollars using the consumer price index (CPI). Only fully employed individuals were selected.[5]

Summary statistics for the sample may be found in Table 2. For the brothers the mean age for "Brother 1" (the elder brother) is 34.17, while the mean age for the younger brother is 31.9 years. The highest grade of schooling attained differs only slightly for the two brothers, with Brother 1 and Brother 2 both possessing on average 13.56 and 13.36 years respectively. Hourly wages are higher for the elder brother, as would be expected from the greater age and education of the elder brother. The correlation in schooling for the two brothers is quite high at .51, while the correlation in log wages is .31.

[5] For the purposes of this study, an individual working an average of 30 hours per week, at least 30 weeks per year, and not enrolled in school, was defined as fully employed. Individuals reporting hourly wages of less than one dollar were excluded.

Table 2 also contains the summary statistics for the father-son sample. For this sample, the mean age for the fathers in 1966 is 50.6 years, while the mean age for the sons in 1981 is 33.26 years. Again, this represents the earliest observation date we could obtain for the fathers and the latest observation date we could obtain for the sons. The difference in observed ages underscores the need to control for lifecycle differences in the reported data. Fathers have considerably less schooling than sons, with highest grade attained being 10.09 years for the fathers and 14.02 years for the sons. Sons also earn about 12% more per hour than fathers. The correlation in father-son schooling is .385 while the correlation in log wages in .364.

III. Empirical Results

Our empirical results are organized as follows: first we report simple least squares estimates for the structural equations and the reduced form equations. These estimates provide the baseline against which to compare other estimates. Next, one brother's (father/son) schooling is used as an instrumental variable for their sibling's (son/father) schooling. This procedure provides a consistent estimator in the presence of measurement error in schooling, but it is not consistent in the presence of an omitted family effect. Finally, we present estimates of the correlated random effects model with and without measurement error and under a variety of over-identifying restrictions.

A. Basic Estimates: Brothers

Table 3 contains the least squares estimates of the structural equations (1) and (2) as well as the reduced form equations (6) and (7) for the sample of brothers. These provide simple estimates of the returns to schooling controlling only for age differences between the two brothers. The results in rows 1 and 3 indicate the returns to schooling to be 5.9% and 7.1% for brothers 1 and 2 respectively.[6] Rows 2 and 4 present the reduced form estimates. In this specification a brother's wage depends on both his own education and that of his brother. As shown in equations (5), (6) and (7) the coefficient of the brother's sibling in the log wage equation provides a measure of the parameter λ_1 or λ_2 from equation (5). As anticipated, these coefficients are positive. They are, however, small in magnitude (λ_1=.018 and λ_2=.006) and statistically insignificant at conventional levels (see column 1 in Table 5). This suggests that estimated returns for brothers are only slightly upward biased due to omitted family background factors. Figure 1.0 presents this basic

6 Interestingly, these estimates are similar to those calculated by Chamberlain and Griliches (in Kinometrics) using the NLS brothers. Chamberlain and Griliches used the sample when most of the brothers were still in school and relied on "expected" occupation to develop their earnings variable and "expected total schooling" for their measure of schooling. Despite these simplifications their results (estimated returns to schooling of 5.7%) are remarkably similar to those ultimately attained by the brothers.

result using a scatter diagram of the intrapair log wage differentials against the intrapair schooling differences. The return to an additional year of education, assuming equal returns for the brothers, (this is the fixed effect estimate - found in Table 5 column 2) is calculated to be 4.7%. Of course, this estimate could be biased downward if there is measurement error in reported schooling.

Table 4 reports the instrumental variables estimate of the return to schooling by using the education of each brother as an instrument for the education of his sibling. As noted above, if the measurement error in brothers schooling is uncorrelated with the true level of schooling, and uncorrelated across brothers, then this instrumental variable would provide a consistent estimate of the returns to schooling if there were no omitted family effect bias. The estimates for the instrumental variables estimator rise to 8% for brother 1 and 8.3% for brother 2.

These results suggest that estimated returns to education do suffer from a small upward omitted variable bias.

B. Correlated Random Effects and Measurement Error: Brothers

Table 5 presents the estimates of the returns to schooling using the correlated random effects framework. Column 1 presents the estimates for the unrestricted model. Returns to schooling are calculated to be 4.6% for brother 1 and 5% for brother 2. These estimates are the same (except for rounding error) as those implied by Table 3. Column 2 presents the estimates restricting the returns to schooling to be the same for both of the brothers. This is the restriction implied by the standard fixed effects model. The estimated (common) return to schooling is 4.7%. Again, λ_1 and λ_2 are insignificant. The Chi-squared statistic for the joint restriction $\beta_1 = \beta_2$ has a p-value of .84. Thus, the fixed effects specification cannot be rejected. Column 3 restricts the λ's to be the same. This hypothesis also cannot be rejected. Finally, column 4 restricts both the returns to schooling to be the same for both brothers and the λ's to be the same. It is not possible to reject this restriction and the resulting estimates closely resemble those of the fixed effects estimator.

Tables 6 and 7 reestimate the correlated random effects specification assuming different magnitudes for the measurement error in reported schooling. We provide estimates using the largest estimated measurement-error-to-total-variance-in-schooling ratio, which was reported by Bielby, Hauser, and Featherman (1977) at $\psi=.199$, and the smallest estimated Ψ reported by Siegel and Hodge (1968) at $\psi=.0668$. We assume measurement error variances are the same for both siblings. As expected, the downward bias in estimated returns to schooling is positively related to the magnitude of the measurement error. Table 11 summarizes the returns to schooling for a range of assumptions about the magnitude of the measurement error. If there is no measurement error estimated returns are 4.6% for brother 1 and 5% for brother 2. If measurement error is as much as 20% of the schooling variance, returns are 7.9% for brother 1 and 8.4% for brother 2. Interestingly, comparing these estimates to the instrumental variables estimates reported earlier suggests that a noise to total variance ratio of .2 seems consistent with the NLS data. This comparison is plausible given the evidence that, for brothers, the estimated returns are not biased downward due to omitted family characteristics.

The fixed effects estimator indicates returns to schooling to be 8% when ψ=.199, compared to the estimate of 4.7% under the assumption of no measurement error.

These estimates of the returns to schooling imply that the upward bias in estimated returns to schooling due to omitted family background factors is fairly small and may be smaller than the downward bias in estimated returns due to measurement error .

C. Basic Estimates: Fathers and Sons

Table 3 contains the least squares estimates of the structural equations (1) and (2) as well as the reduced form equations (6) and (7) for the sample of fathers and sons. The results in rows 3 and 4 indicate the returns to schooling to be 7.5% for the father and 5.7% for the son. The reduced form estimates are found in rows 6 and 8. For fathers and sons the estimated λ_1 and λ_2 parameters are both statistically significant (see column 1 in Table 7) and large. Indeed, the implied structural estimates of the returns to schooling drop from 5.7% to 1.2% for the son. The estimate for the father drops from 7.5% to 5.2%. A scatter diagram of the intrapair log wage differentials against the intrapair schooling differentials is found in Figure 1.0. Here it is apparent that a comparison of two sons, both of whom have educated fathers, the son who is better educated has the higher earnings. The slope of the least squares line drawn through these data (the fixed effects estimate - see column 2 Table 8 for the estimate) indicates that an additional year of schooling results in a 4.5% increase in earnings.

Table 4 investigate the effect of measurement error on returns to schooling by using the education of the father (son) as an instrument for the education of his son (father). The instrumental variables estimates of the returns to schooling are calculated to be 12.7% for the father and 10.9% for the son. These estimates must be regarded with caution, however, as they assume the absence of any omitted variable bias due to family background effects.

These estimates suggest that when using matched father/son data estimated returns may be biased upward by omitted family factors. It is also possible, however, that the assumption of a common family effect is less appropriate in the father/son data. Brothers, for example, would typically be exposed to a similar family environment, while fathers and sons do not grow up in the same household.

D. Correlated Random Effects and Measurement Error: Fathers and Sons

Table 8 presents the results for the correlated random effects model using the father/son data. Column 1 simply separates the structural coefficients implied by the reduced form estimates found in Table 3. As noted above, the λ terms are both positive and significant indicating an omitted variable bias. The fixed effect estimator, which restricts returns to fathers and sons schooling to be the same, is presented in column 2. The (common) estimated return is 4.5% - very similar to that found for the brothers. It is, however, possible to reject the fixed effect restriction for the father and son data. It is also possible to reject the equality of the λ terms.

Tables 9 and 10 reestimate the correlated random effects specification using the estimated measurement error in reported schooling suggested by Bielby et. al and Siegel and Hodge. Table 11 summarizes the estimated returns to schooling for a variety of measurement errors. It may be seen that the returns to son's schooling remain low, even for relatively high level of measurement error.

IV. Conclusions

In this paper we have used matched pairs of brothers and fathers and sons from the National Longitudinal Survey to estimate the economic returns to schooling. Our empirical findings are strongest when using data on brothers. The evidence suggests that any upward bias in estimated returns to schooling due to omitted family background factors is no larger than the downward bias due to errors in the measurement of schooling. Using data on fathers and sons introduces some ambiguity into these findings, as commonly used specification tests reject our simplest models of the role of family background in the determination of earnings. It seems likely that this is due to the role of family income in the determination of the schooling choices of the son, so that a more complex model of the father/son relationship may be necessary for analyzing these data.

Our estimates of the returns to schooling are generally comparable to other estimates in the literature for the time period (1981) for which we measure sibling wage rates. As is well known, the return to schooling has increased substantially in the past decade, so that some care must be taken in the comparison of our results with analyses of other time periods.[7] Perhaps the most comparable earlier study is the Behrman, et. al. 1980 analysis of fraternal twins.[8] Our results are virtually identical to the Behrman, et. al. finding that the intrafamily return to schooling is

[7] See, for example, Katz and Murphy 1992 or Boozer, Krueger, and Wolkon 1992, and, especially for the National Longitudinal Survey data, Blackburn and Neumark 1993.

[8] Fraternal twins of the same sex bear the same genetic relationship as do brothers or sisters.

about 25% lower than the estimate that does not control for unobserved family background differences.

It seems that additional studies of sibling data could provide a useful source of information on the economic returns to schooling. In principle the necessary data should be available to study the returns to schooling for different groups at different time periods and in different locations.

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Table 1

$$(15)\quad \begin{aligned} Y_{1j} &= (\Pi_{11} - \frac{\Pi_{11}\psi_1 - \rho\Pi_{12}\psi_2}{1-\rho^2})X_{1j} \\ &+ (\Pi_{12} - \frac{\Pi_{12}\psi_2 - \rho\Pi_{11}\psi_1}{1-\rho^2})X_{2j} + w_{1j} \end{aligned}$$

$$\begin{aligned} \Rightarrow Y_{1j} &= ((\beta_1 + \lambda_1) - \frac{(\beta_1 + \lambda_1)\psi_1 - \rho\lambda_2\psi_2}{1-\rho^2})X_{1j} \\ &+ (\lambda_2 - \frac{\lambda_2\psi_2 - \rho(\beta_1 + \lambda_1)\psi_1}{1-\rho^2})X_{2j} + w_{1j} \end{aligned}$$

$$(16)\quad \begin{aligned} Y_{2j} &= (\Pi_{21} - \frac{\Pi_{21}\psi_1 - \rho\Pi_{22}\psi_2}{1-\rho^2})X_{1j} \\ &+ (\Pi_{22} - \frac{\Pi_{22}\psi_2 - \rho\Pi_{21}\psi_1}{1-\rho^2})X_{2j} + w_{2j} \end{aligned}$$

$$\begin{aligned} \Rightarrow Y_{2j} &= (\lambda_1 - \frac{\lambda_1\psi_1 - \rho(\beta_2 + \lambda_2)\psi_2}{1-\rho^2})X_{1j} \\ &+ ((\beta_2 + \lambda_2) - \frac{(\beta_2 + \lambda_2)\psi_2 - \rho\lambda_1\psi_1}{1-\rho^2})X_{2j} + w_{2j} \end{aligned}$$

Table 2
Characteristics of Brother and Father-Son Samples

Characteristic:	Mean	Standard Deviation	
Brother sample:			
Brother 1			
Log Hourly Wage	6.79	.460	
Highest Grade	13.56	2.72	
Age		34.17	2.35
Brother 2			
Log Hourly Wage	6.75	.455	
Highest Grade	13.36	2.18	
Age		31.39	1.70
Brother correlation in schooling			.51
Brother correlation in log wages			.31
Sample size			143
Father-son sample			
Father			
Log Hourly Wage	6.69	.507	
Highest Grade	10.09	3.87	
Age		50.6	3.94
Son			
Log Hourly Wage	6.81	.419	
Highest Grade	14.02	2.45	
Age		33.26	2.67
Father-son correlation in schooling			.385
Father-son correlation in log wages			.364
Sample size			332

Table 3

Simple Cross-Section OLS and

Unrestricted Cross-Section OLS Estimates.

	Years of Schooling:			
Dependent Variable: Log Wage:	Brother 1	Brother 2	Father	Son
Brother 1	.059 (.014)	----	----	----
	.052 (.015)	.018 (.020)	----	----
Brother 2	----	.071 (.017)	----	----
	.006 (.015)	.068 (.019)	----	----
Father	----	----	.075 (.006)	----
	----	----	.065 (.006)	.038 (.010)
Son	----	----	----	.057 (.009)
	----	----	.014 (.006)	.049 (.009)

Note: Log wage regressions also include controls for age and age squared.

Table 4

Instrumental Variables Estimates.

Dependent Variable:	Years of Schooling :			
Log Wage :	Brother 1	Brother 2	Father	Son
Brother 1	.080 (.027)	IV	----	----
Brother 2	IV	.083 (.034)	----	----
Father	----	----	.127 (.017)	IV
Son	----	----	IV	.109 (.025)

Note: Log wage regressions also include controls for age and age squared. IV indicates the variable used to instrument for own schooling in regression.

Table 5
Seemingly Unrelated Regression Estimates :
No Measurement Error - Brother Sample.

	Model:			
	Unrestricted	$\beta1=\beta2$(F.E)	$\lambda1=\lambda2$	$\beta1=\beta2$ and $\lambda1=\lambda2$
	(1)	(2)	(3)	(4)
Parameter:				
$\beta1$ - Brother 1	.046 (.019)	——	.045 (.019)	——
$\beta2$ - Brother 2	.050 (.024)	——	.054 (.023)	——
$\beta1$=b2=b	——	.047 (.018)	——	.048 (.018)
$\lambda1$ - Brother 1	.006 (.015)	.005 (.015)	——	——
$\lambda2$ - Brother 2	.017 (.019)	.019 (.017)	——	——
$\lambda1=\lambda2=\lambda$	——	——	.010 (.011)	.011 (.011)
N*Objective	275.98	276.02	276.16	276.34
Prob > χ^2	——	.8415	.6714	.8353

Note: Models also include controls for age and age squared.

Table 6
Seemingly Unrelated Regression Estimates :
Measurement Error ψ=.199 - Brother Sample.

	Model:			
	Unrestricted	$\beta1=\beta2$(F.E)	$\lambda1=\lambda2$	$\beta1=\beta2$ and $\lambda1=\lambda2$
	(1)	(2)	(3)	(4)
Parameter:				
$\beta1$ - Brother 1	.079 (.031)	------	.079 (.031)	------
$\beta2$ - Brother 2	.084 (.037)	------	.087 (.036)	------
$\beta1=\beta2=\beta$	------	.080 (.031)	------	.080 (.031)
$\lambda1$ - Brother 1	-.009 (.025)	-.010 (.024)	------	------
$\lambda2$ - Brother 2	.011 (.030)	.013 (.028)	------	------
$\lambda1=\lambda2=\lambda$	------	------	-.001 (.017)	-.3E-4 (.017)

Note: Models also include controls for age and age squared.

Table 7

Seemingly Unrelated Regression Estimates:

Measurement Error ψ=.0668 - Brother Sample.

	Model:			
	Unrestricted	β1=β2(F.E)	λ1=λ2	β1=β2 and λ1=λ2
	(1)	(2)	(3)	(4)
Parameter:				
β1 - Brother 1	.053	——	.053	——
	(.022)		(.021)	
β2 - Brother 2	.058	——	.061	——
	(.027)		(.026)	
β1=β2=β	——	.055	——	.055
		(.021)		(.021)
λ1 - Brother 1	.003	.002	——	——
	(.017)	(.017)		
λ2 - Brother 2	.016	.018	——	——
	(.022)	(.020)		
λ1=λ2=λ	——	——	.008	.009
			(.013)	(.013)

Note: Models also include controls for age and age squared.

Table 8
Seemingly Unrelated Regression Estimates:
No Measurement Error - Father-Son Sample.

	Model:			
	Unrestricted	$\beta1=\beta2$(F.E)	$\lambda1=\lambda2$	$\beta1=\beta2$ and $\lambda1=\lambda2$
	(1)	(2)	(3)	(4)
Parameter:				
$\beta1$ - Son	.012	-----	.022	-----
	(.012)		(.011)	
$\beta2$ - Father	.052	-----	.051	-----
	(.008)		(.008)	
$\beta1=\beta2=\beta$	-----	.045	-----	.045
		(.008)		(.008)
$\lambda1$ - Son	.038	.020	-----	-----
	(.010)	(.009)		
$\lambda2$ - Father	.014	.017	-----	-----
	(.006)	(.006)		
$\lambda1=\lambda2=\lambda$	-----	-----	.021	.018
			(.005)	(.005)
N*Objective	653.89	665.76	657.77	665.85
Prob > χ^2	----	.0006	.0489	.00256

Note: Models also include controls for age and age squared.

Table 9
Seemingly Unrelated Regression Estimates:
Measurement Error ψ=.199 - Father-Son Sample.

	Model:			
	Unrestricted	$\beta 1=\beta 2$(F.E)	$\lambda 1=\lambda 2$	$\beta 1=\beta 2$ and $\lambda 1=\lambda 2$
	(1)	(2)	(3)	(4)
Parameter:				
$\beta 1$ - Son	.024	-----	.034	-----
	(.016)		(.015)	
$\beta 2$ - Father	.070	-----	.071	-----
	(.011)		(.011)	
$\beta 1=\beta 2=\beta$	-----	.066	-----	.066
		(.011)		(.011)
$\lambda 1$ - Son	.040	.017	-----	-----
	(.014)	(.012)		
$\lambda 2$ - Father	.011	.013	-----	-----
	(.008)	(.008)		
$\lambda 1=\lambda 2=\lambda$	-----	-----	.020	.014
			(.007)	(.007)

Note: Models also include controls for age and age squared.

Table 10

Seemingly Unrelated Regression Estimates:

Measurement Error ψ=.0668 - Father-Son Sample.

	Model:			
	Unrestricted	$\beta1=\beta2$(F.E)	$\lambda1=\lambda2$	$\beta1=\beta2$ and $\lambda1=\lambda2$
	(1)	(2)	(3)	(4)
Parameter:				
$\beta1$ - Son	.015 (.013)	-----	.025 (.012)	-----
$\beta2$ - Father	.057 (.009)	-----	.056 (.009)	-----
$\beta1=\beta2=\beta$	-----	.050 (.009)	-----	.050 (.008)
$\lambda1$ - Son	.039 (.011)	.020 (.009)	-----	-----
$\lambda2$ - Father	.013 (.007)	.016 (.007)	-----	-----
$\lambda1=\lambda2=\lambda$	-----	-----	.021 (.005)	.017 (.005)

Note: Models also include controls for age and age squared.

Table 11

SURE Estimates of Returns to Schooling

For Various Values of ψ.

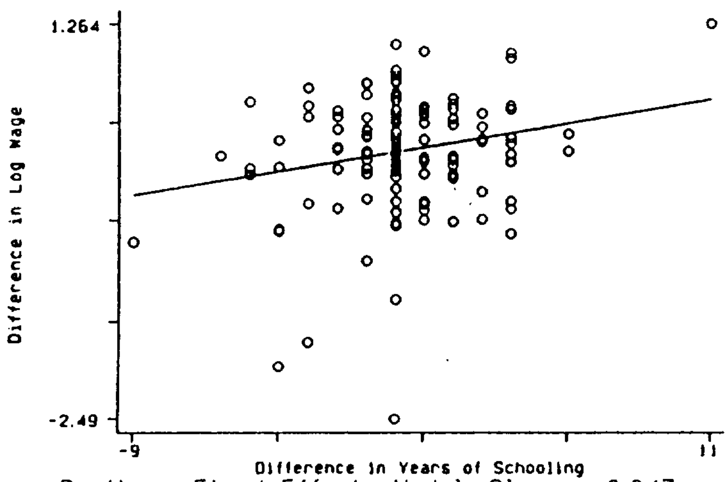
Brother Sample

ψ	$\beta 1$	$\beta 2$
.00	.046	.050
.05	.051	.056
.10	.058	.063
.15	.067	.072
.20	.079	.084
.25	.096	.101
.30	.121	.127

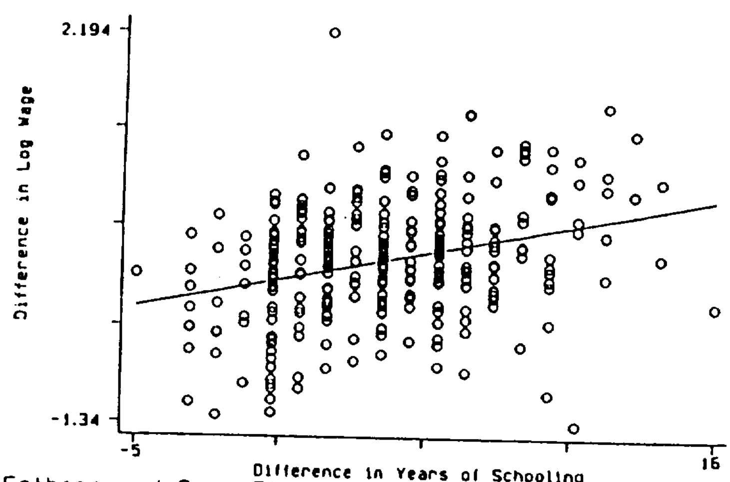
Father-Son Sample

ψ	$\beta 1$	$\beta 2$
.00	.012	.052
.05	.014	.055
.10	.016	.059
.15	.020	.064
.20	.024	.070
.25	.029	.078
.30	.039	.087
.35	.047	.100
.40	.063	.119
.45	.089	.148

Figure 1



Brothers Fixed Effects Model: Slope = 0.047



Fathers and Sons Fixed Effects Model: Slope = 0.045