Estimating the Returns to College Quality with Multiple Proxies for Quality

by

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Abstract

Existing studies of the effects of college quality on earnings typically rely on a single proxy variable for college quality. This study questions the wisdom of this approach given that a single proxy likely measures college quality with substantial error. We begin by considering the parameter of interest and its relation to the parameter estimated in the literature; this analysis reveals the potential for substantial bias. We then consider three econometric approaches to the problem that involve the use of multiple proxies for college quality: combining the multiple proxies via factor analysis, using the additional proxies as instruments, and a GMM estimator derived from a structural measurement error model that generalizes the classical measurement error model. Our estimates suggest that the existing literature understates the wage effects of college quality.

I. Introduction

A growing literature in economics estimates the labor market effects of the quality of the college an individual attends. The literature proceeds by estimating the parameters of linear "education production functions" with an outcome of interest (such as wages) on the left hand side and some measure of college quality (such as the average Scholastic Aptitude Test (SAT) score of the entering class) on the right hand side, usually along with a wealth of covariates designed to take account of non-random selection of students into schools of differing qualities. A related literature performs similar analyses to investigate the effects of primary and secondary school quality. This paper reconsiders the standard education production function literature in a context where multiple measures of college quality are available.

We motivate our analysis in Section II by carefully considering the parameters of interest in studies of college quality and the link between these parameters and the estimates in much of the existing literature. The fundamental issue is that most papers in the existing literature include only a single measure of college quality, which they interpret as a proxy for a latent one-dimensional "college quality" variable. To the extent that the proxy variable measures college quality with error, we expect bias toward zero. Additional bias of unknown direction may arise if we allow the scale of the proxy variable to differ from that of latent college quality. As a result of these issues, existing estimates of the effect of college quality may exhibit substantial biases.

In light of these concerns, our paper considers different ways of using multiple proxies to do better at estimating the impact of college quality than the current literature. After introducing the data and, in particular, our multiple proxies for college quality, in Section III, in Section IV we explicitly model the problem of multiple proxies and derive a measurement error model that allows the variance of each proxy to differ from the variance of unobserved college quality. In Section V, we present four different sets of estimates. First, for comparison purposes, we present

OLS estimates similar to those in the rest of the literature. Second, we combine the information in the proxies using factor analytic methods to produce a college quality index that we then include in the outcome equation. Third, we adopt the standard solution to classical measurement error and use instrumental variables methods, with the additional proxies serving as instruments. Finally, we derive a GMM estimator that identifies, subject to a required normalization, the structural parameters of our more general measurement error model, and we argue for the superiority of this approach on econometric grounds. Section VI reports the results of some sensitivity analyses and Section VII summarizes our contributions and highlights our main finding, which is that the existing literature appears to understate the wage effect of college quality.

II. The Parameter of Interest and the Literature

Consider in somewhat more formal terms the education production function, defined as:

$$Y = f(q_1, ..., q_k, X),$$

where Y denotes an outcome of interest, such as wages, $q_1, ..., q_k$ denote various college level inputs (which we also refer to as measures or dimensions of college quality), such as the average SAT score of the entering class, expenditures per student and so on, and X denotes other factors affecting earnings and college quality choice.

Based on this version of the production function, we can define various parameters of interest; in particular, we can define derivatives with respect to various college level inputs. Consider input k and the usual linear approximation to the production function, so that the parameters of interest become derivatives of the linear conditional expectation function. A

natural parameter of interest is the partial derivative with respect to one dimension of quality, holding the other dimensions (and the X) constant.[1] In notation,

$$P_1 = \frac{\partial E(Y \mid q_1, ..., q_K, X)}{\partial q_k},$$

where P_1 denotes "parameter 1." This parameter is of particular interest to policymakers and college administrators making choices regarding which dimensions to focus on when cutting (to minimize the damage) or adding (to maximize the improvement) to a college budget. Monks (2000) estimates P_1 using data from the National Longitudinal Survey of Youth (NLSY – the same data we employ in this study). Zhang (2005) estimates P_1 for state university systems using the Baccalaureate and Beyond data. Long (2004) estimates this parameter with a very large number of school characteristics in his study of secondary school quality.

The literature on college quality (but not that on primary and secondary school quality) often implicitly adopts the simplifying assumption of a "one factor" model, in which quality has a single dimension. In this case, the production function simplifies to

$$Y = f(Q^*, X),$$

where the variable Q^* is a single factor that we refer to as "college quality." The "*" indicates that the variable is latent. The assumption that Q^* is a scalar is a strong one, as schools may have multiple dimensions, with, for instance, Chicago excelling at liberal arts training and MIT excelling at technical training.

The partial derivative with respect to college quality represents the obvious parameter of interest in the one factor model. In terms of our notation,

$$P_2 = \frac{\partial E(Y \mid Q^*, X)}{\partial Q^*}.$$

[1] We follow the existing college quality literature which treats the slope coefficient on quality as the same across individuals. In a world of heterogeneous slope coefficients, the standard production function regression estimates, under some additional assumptions, what Wooldridge (2002a) calls the Average Partial Effect.

This parameter indicates the effect of an increase in (latent) college quality on the outcome of interest, holding X constant. The one factor model has the virtue of both conceptual simplicity and ease of interpretation in cases where budgetary allocations within a college are not the primary policy issue of interest.

Empirically, aside from Monks (2000), Fitzgerald (2000), Zhang (2005), and our own papers – Daniel, Black and Smith (1995, 1997), Black, Daniel and Smith (2005), and Black and Smith (2004) – most of the literature adopts the following strategy. A single college quality measure q_j is chosen – often some measure of selectivity in admissions – and included in outcome equations along with covariates. Most studies assume what Heckman and Robb (1985) term "selection on observables," in the hope that the inclusion of a sufficiently rich X, including at least some measure of individual "ability" (usually a test score), controls for the non-random matching of students and colleges. Some more recent studies adopt alternative identification schemes that attempt to take account of selection on unobservables. These include the Behrman, Rosenzweig and Taubman (1996) study, which uses data on twins, and the Brewer, Eide and Ehrenberg (1999) study, which uses a parametric polychotomous selection model with variables related to net college costs as exclusion restrictions. Dale and Krueger (2002) represents an intermediate case, because of their access to data on which colleges students applied to and which colleges accepted them, variables not normally observed in studies of this type.

In this paper, we assume selection on observables and focus instead on the issue of how to interpret the parameter estimated in most of the literature; this issue arises regardless of the chosen econometric identification strategy. We can interpret this parameter in three ways, none of which is very satisfactory. First, we can interpret the existing literature as estimating P_3, defined as

$$P_3 = \frac{\partial E(Y \mid q_k, X)}{\partial q_k}.$$

In other words, P_3 denotes the partial derivative of the conditional expectation function with respect to one dimension of quality, holding X but not the other dimensions of quality constant, a parameter that lacks both a clear economic interpretation and any obvious policy relevance. We cannot interpret the literature as estimating P_1 because, as we show in Table 1, the various dimensions of quality have non-trivial positive correlations with one another. As a result, we expect that $P_3 > P_1$. Put differently, when the different dimensions of college quality have positive correlations, including only one dimension means that its coefficient incorporates some of the effects of the other dimensions. (This point holds more generally, and indicates that studies that seek to estimate P_1 require data on all of the relevant inputs to the production function in order to avoid confusing the effects of omitted inputs with those of included inputs). Because P_1 has a clear interpretation while P_3 does not, the necessity of interpreting the existing studies as estimating the latter renders their estimates problematic.

Second, we can interpret the existing studies as estimating P_2, using the single quality measure q_k as a proxy for the latent quality Q^*. This is indeed how most authors in the existing literature interpret what they are doing. For example, Dale and Krueger (2002) treat quality as synonymous with selectivity and interpret the coefficients on their average SAT score variable (or on the *Barron's* magazine quality category dummies that they employ in a separate specification) as estimates of the effect of both quality and selectivity.[2] Other studies talk primarily about selectivity, prestige or competitiveness but clearly intend these as synonyms for quality. Recent papers in this group include Chevalier and Conlon (2003), Fox (1993), Hoxby (1998), and Loury and Garman (1995).

[2] The Barron's college quality categories, which are also used in Brewer, Eide and Ehrenberg (1999), and related categorizations such as the prestige categories in Chevalier and Conlon (2003), raise interesting issues when considered as proxies. Such categorical measures implicitly combine information from multiple measures of college quality (albeit in a less formal way than methods we consider here), which should reduce the amount of measurement error they embody. At the same time, these measures throw out all the variation within categories, which works in the opposite direction.

The second interpretation of the existing literature also raises important conceptual issues. Using only a single proxy variable means that the obtained estimates likely understate the parameter of interest because the proxy variable measures the latent variable with error. The extent of the bias toward zero depends on the extent of measurement error in the proxy variable. Additional biases of unknown direction arise when the proxy variable and the latent variable do not share the same scale. We discuss these scaling issues in more detail below.

The third interpretation treats the observed quality measures as *inputs* into the production of latent quality, rather than as proxies for quality, and then makes some strong assumptions. To begin, assume that all universities and colleges face the same prices and that the underlying college quality production function is homogeneous of degree r in the inputs. Universities pick different levels of quality because of difference in endowments, and, in the case of public universities, because of political constraints. Because the production function is homogeneous of degree r in the inputs and all universities face the same prices, we know that for $\lambda > 0$ inputs differ only by the scale of production or

$$\lambda^r Q^*(q_1,...,q_K) = Q^*(\lambda^r q_1,...,\lambda^r q_K).$$

In this framework, should a researcher enter multiple inputs into the wage equation, the inputs should be perfectly collinear. Indeed, in this framework we need only one input to capture perfectly the production of quality. Under these assumptions, the usual approach in the literature estimates the returns to the latent quality variable.

The very strong, and implausible, assumptions of homogeneity of the production function and common prices derail this approach in our view. We know of no evidence in favor of the homogeneity of this particular production function. It also seems clear that input prices differ among colleges. For example, in the case of student ability, colleges in locations with a large population of highly educated parents and/or with more amenities will face a lower cost of student ability. Finally, this approach requires input measures without error. If, for example,

the average SAT score measures student ability with substantial error, as the large sums spent on admissions offices suggest, then the need for the approaches examined in this paper returns, although the coefficient estimates we obtain have a somewhat different interpretation under these assumptions.

In sum, the existing estimates in the literature present important interpretational difficulties. In our view, they likely represent biased estimates, perhaps substantially biased estimates, of P_2, the usual implicit or explicit parameter of interest in these studies.[3]

III. Data Description

Our data come from three sources. Our primary data source is the National Longitudinal Survey of Youth (NLSY), a panel data set based on surveys of a sample of men and women who were 14-21 years old on January 1, 1979. Respondents were first interviewed in 1979 and were re-interviewed annually from 1979 to 1994 and biannually since 1994. Because we are interested only in the post-college earnings of these respondents, we use earnings data from 1989. We chose 1989 because, given the subsequent attrition in the NLSY, it maximizes our sample size. We limit our sample to men who have attended post-secondary schools for whom we have measures of quality, which is roughly the set of four-year comprehensive colleges and universities.[4] We focus on men to avoid having to deal with labor force participation issues, which are not our primary concern in this paper. See Black and Smith (2004) for more details about the construction of the sample.

[3] See McClellan and Staiger (1999) for a related discussion in the context of measuring hospital quality.

[4] In the course of our earlier work – Daniel, Black, and Smith (1995, 1997) – we compared estimates constructed using all NLSY men and estimates constructed using a sub-sample of those who attended college, where the latter is broader than the sample we employ here because it included individuals who attended colleges for which we do not have quality measures. The substantive results did not differ very much. Despite this, we prefer to err on the side of caution and exclude individuals who either did not attend college or attended a college for which we do not have quality measures in order to avoid having the estimated relationship driven by observations from outside our population of primary interest.

The NLSY suits our purpose well for several reasons. First, the timing means that we have information on wages for a relatively recent cohort of college graduates that is old enough that the vast majority of those who will attend college have already done so. Furthermore, those who will attend graduate school have largely completed doing so as well. Second, the NLSY confidential files provide information on individual colleges attended, which allows us to match up information on specific colleges from external sources. Third, the NLSY allows us to construct a compelling "ability" measure using the Armed Services Vocational Aptitude Battery (ASVAB), which was administered to over 90 percent of the sample.[5] Fourth, the NLSY is rich enough in other covariates to make the assumption that conditioning on observable characteristics alone solves the problem of non-random sorting into colleges of varying qualities plausible. These covariates include detailed information on family background, home environment and high school characteristics.

Our sources for college characteristics are the Department of Education's Integrated Post-secondary Education Data System (IPEDS) for 1992 and the *US News and World Report's Directory of Colleges and Universities* (1991). We only included information for four-year colleges; roughly one half of the men in the NLSY data with some post-secondary education attended a four-year college.[6]

We focus on five measures of quality: faculty-student ratio, the rejection rate among those who applied for admission, the freshman retention rate, the mean SAT score of the entering class, and mean faculty salaries.[7] We focus on these measures for two reasons. First, many of them have been used in previous studies as measures of quality. Second, the response rates for these measures are relatively high, which is important because we limit our sample to individuals

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[5] Neal and Johnson (1996) describe the test in detail and discuss the issues of interpretation surrounding it.

[6] Although the timing of these college quality measures differs somewhat from the timing of college attendance for most of our sample, these measures have a very high serial correlation, so that only a small amount of measurement error likely results from the timing difference.

[7] The first four measures are from the *US News and World Report's Directory of Colleges and Universities* and the last is from the IPEDS data. For schools that report an average ACT score rather than an average SAT score, we impute an SAT score. We redefine the raw college characteristics so that larger values correspond to obvious notions of quality; for example, we recode the "acceptance rate" as a "rejection rate" and use the latter.

whose colleges reported all five measures. The top panel of Table 1 displays the summary statistics for these measures and the bottom panel displays their correlations. The correlations range from a maximum of 0.70 to a minimum of just 0.31.

If each of the quality variables perfectly measured college quality, the correlations would always be one, which they clearly are not. Thus, we must interpret these variables as proxies for college quality, which makes sense. We do not think that a college actually improves if it simply chooses to reject more applicants and does nothing else; instead, in equilibrium the rejection rate provides an indicator for college quality.

Proxy variables are a staple of econometric models; see Wooldridge (2003) and Wooldridge (2002b) for textbook treatments and Bollinger (2003) for further discussion. We refer to the difference between one of our proxy variables and latent college quality as "measurement error."[8] If our proxy variables embody classical measurement error, then every pair among them should have the same covariance (equal to the unknown variance of the latent college quality variable). The data strongly reject this restriction, which indicates that we require a more general measurement error model. The next section outlines such a model.

IV. Econometric Model

The relatively low correlations among the various measures of quality suggest that they contain much measurement error. To focus our discussion, consider the following model of wage determination:

$$\ln(w_{ij}) = X_i \beta + \delta S_i + \gamma Q_{ij}^* + \varepsilon_{ij}, \tag{1}$$

where $\ln(w_{ij})$ is the natural logarithm of the wage rate of the ith person attending the jth college, X_i is a vector of covariates, S_i is the number of years of schooling, Q_{ij}^* is the latent

[8] These variables may not only measure latent college quality with error but also may measure the quantity to which directly correspond with some error, due to data collection or definition problems and to gaming of these measures by the colleges involved. We do not treat this type of measurement error separately here.

quality variable defined in Section III for college j, ε_{ij} is an error term assumed to be uncorrelated with the regressors, and (β, δ, γ) are parameters to be estimated.[9]

The inclusion of years of completed schooling is controversial. As Black and Smith (2004) discuss in some detail, there is a strong correlation between years of college completed and the quality of the institution attended. To the extent that attending a high-quality university increases the number of years of schooling, the model given in equation (1) will understate the returns to attending a high-quality school. To keep our results comparable with the previous literature, however, we will condition on completed years of schooling in this study.

For both schooling and college quality to be plausibly exogenous, we need to condition on a rich set of covariates. Our specification of X_i includes quadratics in the first two principal components of the age-adjusted ASVAB scores as suggested by Cawley, Heckman, and Vytlacil (2001), a black indicator, an Hispanic indicator, a quartic in age, and region of birth dummies.[10] We also include variables measuring home characteristics (whether at age 14 the respondent's household subscribed to a magazine, whether it subscribed to a newspaper, and whether the respondent had a library card), parental characteristics (the years of schooling of each parent, whether the parents were living together in 1979, whether the mother was alive in 1979, whether the father was alive in 1979, and parental occupations in 1978), and high school characteristics (size of the high school, number of books in the library, fraction of the student body that is economically disadvantaged, and mean teacher salary). Rather than dropping observations with

[9] We examined alternative specifications in which college quality entered non-linearly, but found little evidence of departures from linearity. Because it is not the main point of our paper, and because we appear to lack the sample size to precisely estimate a model with non-linear quality effects, we focus on the linear specification in our empirical work.

[10] There is some concern that the ASVAB scores, which were administered to the NLSY sample members around the same calendar time, and thus at different ages and at different points in their schooling, may measure in part differences in either years of schooling or college quality. Using the age-adjusted scores helps to address this issue but does not completely solve it. Hansen, Heckman and Mullen (2004) and Cascio and Lewis (2005) find modest effects of schooling on test scores. In the former case, the evidence is strongest for those in the lower quantiles of the latent ability distribution; in the latter, it is strongest for blacks. Both of these groups comprise only a small fraction of our sample of individuals attending four year colleges. Black and Smith (2004) examined the differential in ASVAB scores between NLSY respondents in the first and fourth quartiles of the college quality distribution as a function of their age at the time of taking the test and found no relationship. Overall, we do not think that this potential problem constitutes much of a real problem for our analysis.

missing values on one or more of the home, parental and high school characteristics due to item non-response, we recode the missing values to zero and add indicators for missing values.

Unfortunately, we do not measure college quality directly but rather must rely on noisy proxies, defined as

$$q_{kj} = \alpha_k Q_j^* + u_{kj}, \tag{2}$$

where $\alpha_k > 0$ is a scale coefficient and u_{kj} is measurement error that we assume is uncorrelated with both Q_j^* and X_i.[11] Our model (modestly) generalizes the classical measurement error model, which requires $q_{kj} = Q_j^* + u_{kj}$. In particular, the inclusion of the scale coefficients allows the covariances of the various proxies, q_{kj}, to differ.[12]

Rather than work directly with equation (1), it is convenient to consider a simple transformation that allows us to ignore the other covariates in equation (1). Let $\ln(\tilde{w}_{ij})$ denote the residual from the regression of $\ln(w_{ij})$ on X_i and S_i and let $\tilde{q}_{ikj}$ denote the residuals from similar regressions of q_{ikj} on X_i and S_i. We refer to $\ln(\tilde{w}_{ij})$, and $\tilde{q}_{ikj}$ as "Yulized residuals" in honor of Yule's (1907) discovery of this decomposition.[13] Using the Yulized residuals, we have

$$\ln(\tilde{w}_{ij}) = \gamma \tilde{q}_{ikj} + \varepsilon_{ij}. \tag{3}$$

Ordinary Least Squares (OLS) or Instrumental Variables (IV) estimation of equation (3) will provide the same estimates of γ as OLS or IV estimation of equation (1). Equation (3), however, provides some insights into the measurement problems. When the covariates explain a substantial portion of the total variation in Q_{ij}^* (by assumption they explain none of variation in u_{kj}), then noise necessarily makes up a larger proportion of the Yulized residuals and the

[11] Our problem is similar to the problems addressed in the MIMIC (Multiple Indicators MultIple Causes) and LISREL frameworks; see, e.g., Jöreskog and Goldberger (1975) and Bollen (1989).

[12] In the regression context, we may also allow the proxies to be of the form $q_k = \beta_k + \alpha_k Q^* + u_k$ without any added complexity; the parameter β_k, however, is not identified.

[13] We thank Terra McKinnish for the reference to Yule's work. See also the discussion of "double residual regression" in Goldberger (1991).

resulting estimates must be attenuated more than when X_i accounts for less of the variation in Q_{ij}^*. As the OLS estimate of γ equals $\mathrm{cov}(\ln(\tilde{w}_{ij}), \tilde{q}_{ikj}) / \mathrm{var}(\tilde{q}_{ikj})$, the more of the variation in Q_{ij}^* that the covariates remove, the larger the noise-to-signal ratio and the greater the attenuation bias in the estimate of γ. While this point has been recognized when dealing with panel data and fixed-effect or first-differenced estimation – see, e.g., Griliches and Hasuman (1986) and Bound and Krueger (1991) – it may not be fully appreciated in a cross-sectional context. Because we condition on a rich set of covariates and because, as we have shown, the various measures of college quality are only modestly correlated, we must be concerned about severe attenuation in estimates that rely on a single proxy. This same concern applies to most of the other college quality studies in the literature.

V. Estimates

A. OLS Estimates

In column (1) of Table 2, we report estimates from a model that includes all five proxies for college quality. None of the five coefficient estimates differ significantly from zero at conventional levels, despite that fact that we use one-tailed tests (both here and throughout the tables) given the nature of our null hypothesis. Given equations (2) and (3), however, this is hardly surprising. Identification of the parameters on the college quality measures rests on components that are orthogonal to the other quality measures. If the single factor model is correct, the Yulized residuals of the quality measures (which now condition on the other quality measures in each case, as well as on *X* and *S*) will asymptotically only contain the measurement error. Thus, in the context of the single factor model, including multiple proxies makes little sense.

In columns (2) through (6), we report estimates from regressions that include each one of the proxy variables in turn. When entering the equation alone, the estimated coefficient for each

of the measures exceeds – usually substantially – the corresponding coefficient when the variables enter jointly. To provide the reader with a notion of the economic magnitude of the coefficients, in brackets we present the impact on log wages of moving from the 25th to the 75th percentile of each quality measure. When entered alone, three of the five coefficients are statistically significant. Moreover, the statistically significant estimates are economically meaningful: moving from the 25th to the 75th increases wages from over 4.3 to over 6.3 percent. To give a sense of what this means, in the five-variable factor model presented in the next section, this means moving from Wright State University (in Ohio) to the University of Iowa.

In the context of our model, however, these estimates may be quite attenuated. As is well known, classical measurement error generally attenuates the coefficient estimates. As our discussion of the Yulized residuals demonstrates, estimation of a model that includes a rich set of covariates exacerbates the attenuation bias, because the covariates explain a portion of Q_{ij}^{*} but none of the error term u_{ikj}, and so increase the noise-to-signal ratio. This effect has empirical relevance in our context; when we regress each quality measure on X_i and S_i, we account for 18 percent of the variation in the faculty-student ratio, 24 percent of the variation in the rejection rate, 29 percent of the variation the freshman retention rate, and 25 percent of the variation in average SAT scores and average faculty salaries. Of course, we cannot solve this problem by simply dropping variables from the model, because only a rich covariate set makes our "selection on observables" identification strategy plausible.

Given the modest correlations among the quality measure in Table 1, removing a substantial fraction of the systematic variation may lead to a lot of attenuation. To see why, we note that under our form of nonclassical measurement error

$$\text{plim}\hat{\gamma}^{OLS} = \frac{\gamma}{\alpha_k}\left(1 + \frac{\text{var}(\tilde{u}_{jki})}{\alpha_k^2 \,\text{var}(\tilde{Q}_{ji}^{*})}\right)^{-1}, \tag{4}$$

where $\tilde{u}_{ikj}$ and $\tilde{Q}^*_{ij}$ are the Yulized residuals from the regression of q_{ikj} on (X_i, S_i) and $\mathrm{var}(\tilde{u}_{ikj}) / \alpha_k^2 \, \mathrm{var}(\tilde{Q}^*_{ij})$ is the noise-to-signal ratio. Now suppose that for the average SAT scores and freshman retention rates we have that $\alpha_k = 1$ so that the measurement error is classical, and suppose that $\mathrm{var}(Q^*_{ij}) = 1$. If we assume both measures have the same $\mathrm{var}(\tilde{u}_{jki})$, the correlation of 0.702 implies that the OLS estimate is only 0.702 of the correct magnitude if Q^*_{ij} is orthogonal to the other covariates (X_i and S_i) in the model. If the other covariates reduce the variation in the average SAT score by 25 percent (and all of the reduction comes from the signal), then the parameter estimate is only about 0.602 of the correct magnitude. The additional attenuation bias from the covariates increases when the covariates explain more of the systematic component of college quality.

Equation (4) is also useful to see the fundamental identification problem faced when using proxy variables. Even in the absence of measurement error, so that $\mathrm{var}(\tilde{u}_{jki}) = 0$, the OLS estimate will be biased unless $\alpha_k = 1$. In the presence of measurement error, we cannot determine whether the estimates are biased upward or downward. For instance, when $\alpha_k < 1$, the estimates may be biased upward despite the attenuation bias that results from the measurement error.

We believe that the failure to model this scale factor may be of first-order importance. For instance, few would dispute that the average SAT score of the entering class would be correlated with the quality of a college or university. Indeed, many authors use this as their sole measure of college quality. It is another matter, however, to assert without corroborating evidence that this measure varies on the same scale as college quality.[14]

[14] Bollinger (2003) notes the fundamental nonidentification problem when there is a single proxy and derives bounds the coefficient γ / α.

B. Factor Analysis Estimates

Intuitively, we should be able to combine the various measures of college quality to obtain a more reliable measure of Q^*. More formally, suppose that across all colleges, $E(Q_j^*)=0$, a harmless normalization that keeps the notation simple. Let $q=(q_1,...,q_K)'$ be a *K*-vector of noisy signals of the quality of each college, such that for a college with quality Q_j^*, the value of each signal is $q_{kj}=\alpha_k Q_j^*+u_{kj}$ with $E(q_{kj})=0, E(u_{kj}^2)=\sigma_k^2,\ E(u_{kj}u_{kh})=0\,\forall j\neq h$, $E(u_{kj}u_{lj})=0\,\forall k\neq l$, and $E(Q_j^* u_{kj})=0$.[15] We construct a measure of college quality by taking a linear combination of the signals. Define $\hat{Q}\equiv\sum_{k=1}^{K}\tau_k q_k$, where there is no need for an intercept term because the expected value of Q_j^* is normalized to zero. We select the τ_k to minimize the expected squared distance between $\hat{Q}$ and Q^*, or

$$\min_{\tau_1,...,\tau_K} E(Q^*-\hat{Q})^2. \tag{5}$$

The necessary conditions for minimization are

$$\alpha_k \operatorname{var}(Q^*)-\alpha_k\sum_{l=1}^{K}\alpha_l\tau_l \operatorname{var}(Q^*)-\tau_k\sigma_k^2=0 \quad \forall k\in\{1,2,...,K\}, \tag{6}$$

or

$$1-\sum_{l=1}^{K}\alpha_l\tau_l-\alpha_k\tau_k r_k=0 \quad \forall l\in\{1,2,...,K\}, \tag{7}$$

where r_k is the noise-to-signal ratio $\dfrac{\sigma_k^2}{\alpha_k^2\operatorname{var}(\tilde{Q}^*)}$. Evaluating equation (7) at $k=1$ and $k=l$ implies that

$$\alpha_l\,\tau_l=\alpha_1\,\tau_1\frac{r_1}{r_l}. \tag{8}$$

Thus, we may rewrite equation (7) as

[15] Lubotsky and Wittenberg (2004) extend the factor analysis framework to the case of correlated measurement error among the proxy variables and derive a lower bound on the parameter of interest in that context.

$$\alpha_1^{-1} r_1^{-1} - \tau_1 \left(\sum_{l=1}^{K} r_l^{-1} + 1 \right) = 0 \ . \tag{9}$$

Solving for τ_1 we obtain

$$\tau_1 = \frac{\alpha_1^{-1} r_1^{-1}}{1 + \sum_{l=1}^{K} r_l^{-1}} \ . \tag{10}$$

The remaining τ_k have similar formulae. Thus, τ_k decreases in the variance of the idiosyncratic error u_k, so that signals that more accurately reflect the latent college quality receive more weight in the forecast.

Readers familiar with the psychometrics literature may recognize this model as a transformation of Spearman's (1904) factor model; see Harman (1976) for a good discussion of the historical development of this model. To implement the model, we simply specify the signals to be used in the factor analysis.[16] In the spirit of Carniero, Hansen, and Heckman (2003), we also looked for a second factor. We found a second factor only in the case of the five-variable model; in that case, we tried including the second factor in the regression model and could not reject the null of a zero coefficient. Thus, we report only results based on first factors in all cases. The implied college quality rankings based on the first factors accord with a priori notions of quality; for example, Stanford, Harvard, MIT, Yale and Penn comprise the top five schools attended by respondents in our sample based on the five-variable model. The first factors obtained using different combinations of variables correlate strongly with one another, as expected. For the two-variable factors, the correlations range from 0.53 to 0.90, while for the three- and four-variable models the correlations range between 0.73 and 0.98 and 0.96 and 0.99, respectively.

[16] We estimated the factor loadings using both the sample of schools attended by individuals in our analysis sample and the sample of all schools attended by anyone in the NLSY data. The factor loadings differed little between the two samples; the estimates in Table 2 are based on the first set of factor loadings.

After obtaining the factor loadings, we estimate equation (1) with OLS, with the quality index included as the quality measure. In Table 3, we provide factor analysis estimates from a variety of two-, three-, four-, and five-signal models. Generally, the estimates are increasing in magnitude – as measured by the impact of moving from the 25th to the 75th percentile of the factor – when we increase number of signals used, as is expected when the signals contain measurement error. For example, the estimates with two proxies range from 0.30 to 0.63, those with three from 0.47 to 0.61, those with four from 0.50 to 0.61 and the estimate using all five proxies equals 0.49. The estimates nearly always exceed four of the five simple OLS estimates presented in Table 2, as they should given that this procedure uses additional information to obtain a better proxy for Q^*.[17]

The factor analysis approach is simple to implement and makes it easy to construct a quality index for use in ranking colleges. At the same time, the factor analysis estimates remain attenuated relative to the true value because the use of multiple signals lowers but does not eliminate the resulting measurement error.[18] Thus, we now turn to an alternative in the form of instrumental variables.

C. Instrumental Variables Estimates

Economists have long recognized that instrumental variables estimation may eliminate the bias associated with estimates obtained using variables with classical measurement error. See Griliches (1986) for a review of the early literature, and see Bound, Brown, and Mathiowetz (2001) for a more recent review of the literature. Black, Berger, and Scott (2000), Kane, Rouse, and Staiger (1999), and Frazis and Loewenstein (2003) all document that standard IV estimation may be upwardly biased in the presence of nonclassical measurement error.

[17] The estimated standard errors in Table 3 do not reflect a correction for the estimation of the factor loadings.
[18] Factor analysis provides an unbiased estimate of the underlying latent variable even when only two variables are used to construct the factor. Adding additional variables to the factor analysis reduces the variance of the resulting estimate of the latent variable, meaning that, on average, it contains less measurement error. This in turn reduces attenuation bias in the estimated regression coefficient in the outcome equation.

With our slightly more general form of measurement error, standard IV estimation also will not provide point identification. To see why, we note that the IV estimator with a single instrument is

$$\hat{\gamma}^{IV} = \frac{\sum_{i=1}^{N} \tilde{q}_{kji} \ln(\tilde{w}_{ij})}{\sum_{i=1}^{N} \tilde{q}_{kji} \tilde{q}_{lji}} , \tag{11}$$

where i indexes observations and (q_l, q_k) are two of the quality measures. Taking the probability limit of the IV estimator we obtain

$$\text{plim}\, \hat{\gamma}^{IV} = \gamma \frac{\alpha_k Var(\tilde{Q}^*)}{\alpha_k \alpha_l Var(\tilde{Q}^*)} = \frac{\gamma}{\alpha_l}. \tag{12}$$

The inclusion of more instruments does not remedy the inconsistency. Hence, the parameter of interest is only identified up to a positive constant. Of course, even if we assume there is no measurement error, so that $\sigma_1^2 = \sigma_2^2 = ... = \sigma_n^2 = 0$, standard OLS only identifies the parameter of interest up to a positive constant as well. The difference, however, is that moving from, say, the 25th percentile of the (non-noisy) measure to the 75th percentile moves one from the 25th percentile of quality to the 75th percentile of quality; with measurement error, that property disappears, and the resulting estimates become substantially less interpretable.

With that caveat, in Table 3 we present IV estimates where we use one quality measure in the "structural equation" and the remaining four measures as instruments. Each of the estimates is statistically significant, and much larger than the corresponding OLS estimate. The IV estimates, which range from 0.77 to 0.93 for the effect of moving from the 25th percentile of quality to the 75th percentile, also substantially exceed the factor analysis estimates.

Asymptotically, the OLS and IV estimates differ by the term

$$\left(1 + \frac{\text{var}(\tilde{u}_{ki})}{\alpha_k^2 \,\text{var}(\tilde{Q}_i^*)}\right)^{-1},$$

which is strictly increasing in the noise-to-signal ratio. Using this observation, we estimate that the faculty-student ratio is the noisiest measure of school quality and the freshman retention rate is the least noisy measure. Given that the IV estimator identifies the parameter of interest only up to scale, we now turn our attention to a final estimator, which does identify the parameter of interest, subject only to a modest normalization.[19]

D. Method of Moments Estimates with a Convenient Normalization

When we have two quality measures, we are unable to identify the general measurement error model presented in Section IV from the covariance matrix of the data. To see why, consider the covariance matrix of the data given by

$$\begin{aligned}
&\mathrm{var}(\ln(\tilde{w})) = \gamma^2\sigma^2_{\tilde{Q}^*} + \sigma^2_{\tilde{\varepsilon}}, \\
&\mathrm{var}(\tilde{q}_k) = \alpha_k^2\sigma^2_{\tilde{Q}^*} + \sigma^2_k, \qquad k = 1,2,...,K; \\
&\mathrm{cov}(\ln(\tilde{w}), \tilde{q}_k) = \gamma\,\alpha_k\,\sigma^2_{\tilde{Q}^*}, \qquad k = 1,2,...,K; \\
&\mathrm{cov}(\tilde{q}_k, \tilde{q}_l) = \alpha_k\alpha_l\sigma^2_{\tilde{Q}^*}, \qquad k,l = 1,2,...,K, k \neq l.
\end{aligned} \tag{13}$$

The number of equations in this system is $2K + 1 + \sum_{l=1}^{K-1} l$, where K is again the number of quality measures. The number of unique parameters the system contains is $(3 + 2K)$.

Consider the case with $K = 2$. In this case we have six equations and seven parameters, so that the system is underidentified. We do not, of course, ever observe Q^*, which suggests normalizing $\sigma^2_{\tilde{Q}^*}$ to one. Doing so reduces the number of parameters to six, so that the three "off-diagonal" elements of the covariance matrix now suffice to identify $(\alpha_1, \alpha_2, \gamma)$. It is easy to show that:

[19] We could combine the factor analysis and IV approaches by constructing the index with some of the proxies and then instrumenting it using the remaining ones. This approach does not, however, solve the problems associated with using either of the methods separately.

$$\alpha_1 = \frac{\left(\mathrm{cov}(\ln(\hat{w}),\tilde{q}_1)\,\mathrm{cov}(\tilde{q}_1,\tilde{q}_2)\right)^{1/2}}{\left(\mathrm{cov}(\ln(\hat{w}),\tilde{q}_2)\right)^{1/2}},$$
$$\alpha_2 = \frac{\left(\mathrm{cov}(\ln(\hat{w}),\tilde{q}_2)\,\mathrm{cov}(\tilde{q}_1,\tilde{q}_2)\right)^{1/2}}{\left(\mathrm{cov}(\ln(\hat{w}),\tilde{q}_1)\right)^{1/2}}, \tag{14}$$
$$\gamma = \frac{\left(\mathrm{cov}(\ln(\hat{w}),\tilde{q}_1)\,\mathrm{cov}(\ln(\hat{w}),\tilde{q}_2)\right)^{1/2}}{\left(\mathrm{cov}(\tilde{q}_1,\tilde{q}_2))\right)^{1/2}}.$$

In the factor analysis estimator, the covariances between the individual proxy variables and the wage play a role only indirectly via the correlation between the quality index and the wage, whereas the GMM estimator makes use of these covariances directly.

Now consider $K > 2$. We might hope that additional proxies would allow us to identify the entire system without a normalization, but this turns out not to be possible. To see why, consider the off-diagonal equations

$$\begin{aligned} &\mathrm{cov}(\ln(\tilde{w}),\tilde{q}_k) = \gamma\,\alpha_k\,\sigma^2_{\tilde{Q}^*}, && k = 1,2,\ldots,K; \\ &\mathrm{cov}(\tilde{q}_k,\tilde{q}_l) = \alpha_k\alpha_l\sigma^2_{\tilde{Q}^*}, && k,l = 1,2,\ldots,K, k \neq l. \end{aligned} \tag{15}$$

By way of contradiction, suppose that $(\hat{\alpha},\hat{\gamma},\hat{\sigma}^2_{\tilde{Q}^*})$ represents a unique solution to the system. The vector $(\frac{\hat{\alpha}}{\sqrt{c}},\frac{\hat{\gamma}}{\sqrt{c}},c\hat{\sigma}^2_{\tilde{Q}^*})$, for an arbitrary $c > 0$ also solves the system. Hence, the solution is not unique, which contradicts the hypothesis. Of course, this result is hardly surprising; we have no data on Q^* so we are unable to identify its moments.

When we normalize the variance of Q^* to one, the system becomes over-identified for $K > 2$ and we can use optimally weighted GMM to estimate the system; see Wooldridge (2002b) for a discussion. The GMM estimator avoids both the inconsistency associated with the factor analysis estimator and the strong assumptions about the scales of the proxy variables required to justify the IV estimator; for this reason, we strongly prefer it on econometric grounds. At the same time, we note that, unlike the factor analysis approach, it does not provide a handy quality ranking of colleges as a byproduct.

Using the five covariances with the wage measure and the 10 covariances of the college quality proxies, we estimate $\gamma = 0.043$, with a standard error of 0.0164. Thus, as shown in Table 4, an increase of 1.34 standard deviations in college quality, which would roughly correspond to a movement from the 25th to the 75th percentile if college quality were normally distributed, would result in an increase of about 0.056 in log wages.

Our GMM estimate of 0.056 exceeds four of the five OLS estimates in Table 2. In particular it exceeds the estimate obtained using the average SAT score variable, which is the most common variable used in the literature, by over 20 percent. This suggests that the existing literature understates the labor market effects of college quality. The GMM estimate is similar to many of the estimates from the factor analysis, and smaller than that obtained using IV methods. This latter finding suggests that scale issues play a role here, and serve to partially undo the attenuation bias resulting from the measurement error.

Table 4 also displays the implied noise-to-signal ratios for each of the college quality measures. The least noisy proxy for college quality is average SAT, which supports the frequent use of this variable in the literature. The next least noisy is the freshman retention rate, followed by average faculty salaries, the rejection rate, and the faculty-student ratio, where the last two are noisy indeed.

VI. Sensitivity Analyses

We performed three sensitivity analyses on our estimates. First, because of the sensitivity of standard GMM to the estimation of the covariance matrix documented by Altonji and Segal (1996), we calculated the equally weighted minimum distance estimator. This estimator yields an estimate of $\gamma = 0.042$, which differs from the optimally weighted GMM estimate by only 0.01.

Second, we calculated the GMM estimate using all possible observations to calculate each moment condition, rather than using the subset of observations with valid values for all of the variables used in constructing the estimate. The benefit from this procedure comes from not throwing out information, the downside is that the variables are likely not missing at random, which is what is required for this procedure to produce consistent estimates. Compared to the sample of 887 observations with valid values for all of the variables, the number of observations used ranges from 911 for SAT scores and wages to 1593 for faculty salaries and wages, where the 911 and 1593 do not fully overlap. This wide variation in the observations utilized in each case provides plenty of scope for selection issues to arise. As a result, we do not put too much weight on the resulting estimate of $\gamma = 0.036$, but it does suggest the value of filling in the data to create a large sample with valid values for all of the variables.

Finally, we calculated the GMM estimate using 1998 wages rather than 1989 wages. This reduces the sample size to 707, and yields an estimate of $\gamma = 0.038$.[20]

VII. Conclusions

Our analysis shows that much of the existing literature likely underestimates the labor market effects of college quality as a result of using a single quality variable as a proxy for the true, unobserved college quality. Our GMM estimator, which builds on a generalization of the classical measurement error model and makes use of information on four additional proxies for college quality, suggests that existing estimates understate the effect of college quality by around 20 percent. This is not a huge effect but it is not a trivial one either; given the easy availability of additional proxies there is little excuse not to use them.[21]

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[20] The OLS, factor analysis, and IV estimates using the 1998 data also resemble their counterparts from the 1989 data.

[21] Our analysis suggests that the quality variables commonly used in the primary and secondary school literature, such as class size (often measured at the school or district level and so with substantial error), teacher experience

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and whether or not the teacher has an advanced degree constitute weak proxies for (unobserved) school quality. Moreover, to the extent that these variables covary with dimensions of school quality not included in the model, they overstate the effects of these variables, holding the others constant, which is the policy parameter of interest in these papers. This interpretation comports with the findings of Rivkin, Hanushek, and Kain (2004), who estimate a very large variance of teacher quality not accounted for by observable teacher characteristics.

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Table 1: Means and Correlations Between Quality Variables, NLSY Men 1989

	Mean	Standard Deviation	Minimum value	Maximum value
Faculty-student ratio	0.0663	0.0264	0.02	0.25
Rejection rate	0.255	0.165	0	0.82
Freshman retention rate	0.750	0.123	0.24	0.98
Mean SAT score/100	9.36	1.44	5.50	13.75
Mean faculty salaries /1,000,000	0.0550	0.0107	0.0236	0.0958

N = 887

	Faculty-student ratio	Rejection rate	Freshman retention rate	Mean SAT score	Mean faculty salaries
Faculty-student ratio	1.000	---	---	---	---
Rejection rate	0.313	1.000	---	---	---
Freshman retention rate	0.342	0.478	1.000	---	---
Mean SAT score	0.397	0.535	0.702	1.000	---
Mean faculty salaries	0.396	0.449	0.613	0.674	1.000

Notes: Authors' calculations, NLSY data, *US News and World Report's Directory of Colleges and Universities*, and IPEDS data. College quality measure is for last college attended as of 1989.

Table 2: Impact Estimates from Regressions with Each Quality Variable Individually and with All Quality Variables NLSY Men 1989

	(1)	(2)	(3)	(4)	(5)	(6)
Faculty-student ratio	0.475 (0.6193) [0.009]	0.962 (0.5945) [0.018]	---	---	---	---
Rejection rate	0.020 (0.1208) [0.004]	---	0.157 (0.1123) [0.028]	---	---	---
Freshman retention rate	0.310 (0.2188) [0.050]	---	---	**0.395** **(0.1619)** **[0.063]**	---	---
Mean SAT score/100	0.001 (0.0161) [0.002]	---	---	---	**0.025** **(0.0120)** **[0.046]**	---
Mean faculty salaries /1,000,000	0.725 (2.213) [0.010]	---	---	---	---	**3.22** **(1.849)** **[0.047]**
N	887	887	887	887	887	887

Notes: Authors' calculations using NLSY data, *US News and World Report's Directory of Colleges and Universities*, and IPEDS data. College quality measure is for last college attended as of 1989. The regressions also include years of schooling, quadratics in the first two principal components of the age-adjusted AFQT scores, a black indicator, a Hispanic indicator, a quartic in age, and region of birth dummies. We also include controls for home characteristics (whether at age 14 the household subscribed to a magazine, whether it subscribed to a newspaper, and whether the respondent had a library card), parental characteristics (education of the parents, whether their parents were living together in 1979, whether the mother was alive in 1979, whether the father was alive in 1979, and parental occupations in 1978), and high school characteristics (size of high school, number of books in the school library, fraction of student body that was economically disadvantaged, and mean teachers' salaries). To avoid losing sample due to missing values resulting from item non-response, we recoded the home, parental, and high school characteristics missing values to zero and then added indicator variables that equal one if the corresponding data element is missing. The dependent variable is the natural log of the respondent's wage, defined as earnings in 1988 (the year prior to the 1989 survey) divided by hours in 1988. The values in brackets indicate the return from moving from the 25th percentile of the quality measure to the 75th percentile. Huber-White standard errors appear in parentheses. Bold type indicates significance at the five-percent level in a one-tailed test.

Table 3: Estimates from Regressions Including College Quality Indices Constructed using Factor Analysis NLSY Men 1989

Panel A: Two measure models

Factor combines faculty-student ratio and rejection rate	**0.060** **(0.0323)** **[0.030]**	Factor combines rejection rate and mean SAT scores	**0.050** **(0.0255)** **[0.045]**
Factor combines faculty-student ratio and freshman retention files	**0.080** **(0.0331)** **[0.042]**	Factor combines rejection rate and mean faculty salaries	**0.054** **(0.0303)** **[0.045]**
Factor combines faculty-student ratio and mean SAT scores	**0.061** **(0.0278)** **[0.037]**	Factor combines freshman retention rates and mean SAT scores	**0.056** **(0.0225)** **[0.063]**
Factor combines faculty-student ratio and mean faculty salaries	**0.060** **(0.0289)** **[0.038]**	Factor combines freshman retention rates and mean faculty salaries	**0.062** **(0.0264)** **[0.060]**
Factor combines rejection rate and freshman retention rates	**0.064** **(0.0287)** **[0.052]**	Factor combines mean SAT scores and mean faculty salaries	**0.049** **(0.0238)** **[0.053]**

Table 3 (Continued)

Panel B: Three measure models

Factor combines faculty-student ratio, rejection rate, and freshman retention rate	**0.059 (0.0244) [0.057]**	Factor combines rejection rate, freshman retention rate, and mean SAT score	**0.048 (0.0202) [0.059]**
Factor combines faculty-student ratio, rejection rate, and mean SAT score	**0.046 (0.0212) [0.047]**	Factor combines rejection rate, freshman retention rate, and mean faculty salaries	**0.055 (0.0234) [0.060]**
Factor combines faculty-student ratio, rejection rate, and mean faculty salaries	**0.048 (0.0241) [0.049]**	Factor combines freshman retention rate, mean SAT score, and mean faculty salaries	**0.050 (0.0208) [0.061]**

Panel C: Four measure models

Factor combines faculty-student ratio, rejection rate, freshman retention rate, and mean SAT scores	**0.049 (0.0203) [0.059]**	Factor combines faculty-student ratio, freshman retention rate, mean SAT scores, and mean faculty salaries	**0.051 (0.0209) [0.061]**
Factor combines faculty-student ratio, rejection rate, freshman retention rate, and mean faculty salaries	**0.055 (0.0233) [0.060]**	Factor combines rejection rate, freshman retention rate, mean SAT scores, and mean faculty salaries	**0.049 (0.0208) [0.057]**
Factor combines faculty-student ratio, rejection rate, mean SAT scores, and mean faculty salaries	**0.046 (0.0211) [0.050]**		

Panel D: Five measure model

Factor combines faculty-student ratio, rejection rated, freshman retention rate, mean SAT scores, and mean faculty salaries	**0.042 (0.0170) [0.049]**

Notes: Authors' calculations using NLSY data, *US News and World Report's Directory of Colleges and Universities*, and IPEDS data. College quality measure is for last college attended as of 1989. The regressions also include years of schooling, quadratics in the first two principal components of the age-adjusted AFQT scores, a black indicator, a Hispanic indicator, a quartic in age, and region of birth dummies. We also include controls for home characteristics (whether at age 14 the household subscribed to a magazine, whether it subscribed to a newspaper, and whether the respondent had a library card), parental characteristics (education of the parents, whether their parents were living together in 1979, whether the mother was alive in 1979, whether the father was alive in 1979, and parental occupations in 1978), and high school characteristics (size of high school, number of books in the school library, fraction of student body that was economically disadvantaged, and mean teachers' salaries). To avoid losing sample due to missing values resulting from item non-response, we recoded the home, parental, and high school characteristics missing values to zero and then added indicator variables that equal one if the corresponding data element is missing. The dependent variable is the natural log of the respondent's wage, defined as earnings in 1988 (the year prior to the 1989 survey) divided by hours in 1988. The values in brackets indicate the return from moving from the 25th percentile of the quality measure to the 75th percentile. Huber-White standard errors appear in parentheses. Bold type indicates significance at the five-percent level in a one-tailed test. There are 887 observations in each regression. We construct each college quality index using factor analysis.

Table 4: IV Estimates of the Effect of College Quality NLSY Men 1989

	(1)	(2)	(3)	(4)	(5)
Faculty-student ratio	**4.07** **(1.942)** **[0.077]**	---	---	---	---
Rejection rate	---	**0.512** **(0.2134)** **[0.092]**	---	---	---
Freshman retention rate	---	---	**0.483** **(0.2281)** **[0.077]**	---	---
Mean SAT score/100	---	---	---	**0.045** **(0.0185)** **[0.083]**	---
Mean faculty salaries /1,000,000	---	---	---	---	**6.46** **(2.666)** **[0.093]**
Corresponding OLS estimate of quality measure	0.962 (0.5945)	0.157 (0.1123)	**0.395** **(0.1619)**	**0.025** **(0.0120)**	**3.22** **(1.849)**
Partial F-statistic instruments from first-stage regression {p-value}	22.5 {0.000}	55.4 {0.000}	231.8 {0.000}	246.3 {0.000}	134.7 {0.000}
N	887	887	887	887	887

Notes: Authors' calculations using NLSY data, *US News and World Report's Directory of Colleges and Universities*, and IPEDS data. College quality measure is for last college attended as of 1989. The regressions also include years of schooling, quadratics in the first two principal components of the age-adjusted AFQT scores, a black indicator, a Hispanic indicator, a quartic in age, and region of birth dummies. We also include controls for home characteristics (whether at age 14 the household subscribed to a magazine, whether it subscribed to a newspaper, and whether the respondent had a library card), parental characteristics (education of the parents, whether their parents were living together in 1979, whether the mother was alive in 1979, whether the father was alive in 1979, and parental occupations in 1978), and high school characteristics (size of high school, number of books in the school library, fraction of student body that was economically disadvantaged, and mean teachers' salaries). To avoid losing sample due to missing values resulting from item non-response, we recoded the home, parental, and high school characteristics missing values to zero and then added indicator variables that equal one if the corresponding data element is missing. The dependent variable is the natural log of the respondent's wage, defined as earnings in 1988 (the year prior to the 1989 survey) divided by hours in 1988. The values in brackets indicate the return from moving from the 25th percentile of the quality measure to the 75th percentile. Huber-White standard errors appear in parentheses. Bold type indicates significance at the five-percent level in a one-tailed test.

Table 5: GMM Estimates of the Effect of College Quality and Noise-to-Signal Ratios for the College Quality Measures NLSY Men 1989

	Estimates
γ	**0.043** **(0.0164)** **[0.056]**
Noise-to-signal ratio for faculty-student ratio	5.83
Noise-to-signal ratio for rejection rate	2.30
Noise-to-signal ratio for freshman retention rate	0.798
Noise-to-signal ratio for mean SAT score	0.383
Noise-to-signal ratio for mean faculty salaries	0.955
N	887

Notes: Authors' calculations using NLSY data, *US News and World Report's Directory of Colleges and Universities*, and IPEDS data. College quality measure is for last college attended as of 1989. The regressions also include years of schooling, quadratics in the first two principal components of the age-adjusted AFQT scores, a black indicator, a Hispanic indicator, a quartic in age, and region of birth dummies. We also include controls for home characteristics (whether at age 14 the household subscribed to a magazine, whether it subscribed to a newspaper, and whether the respondent had a library card), parental characteristics (education of the parents, whether their parents were living together in 1979, whether the mother was alive in 1979, whether the father was alive in 1979, and parental occupations in 1978), and high school characteristics (size of high school, number of books in the school library, fraction of student body that was economically disadvantaged, and mean teachers' salaries). To avoid losing sample due to missing values resulting from item non-response, we recoded the home, parental, and high school characteristics missing values to zero and then added indicator variables that equal one if the corresponding data element is missing. The dependent variable is the natural log of the respondent's wage, defined as earnings in 1988 (the year prior to the 1989 survey) divided by hours in 1988. The values in brackets indicate the return from moving from the 25th percentile of the quality measure to the 75th percentile. Huber-White standard errors appear in parentheses. Bold type indicates significance at the five-percent level in a one-tailed test.
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