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Abstract

Traditional studies of returns-to-schooling have been generally concerned with several issues like the omitted variable bias, error-in-measurement bias and the endogeneity of schooling. While such inquiries are of much empirical importance, this paper tries to ask a different but non-negligible question: what should be interpreted from the individual ability measure per se in the wage equation? With data from well documented national surveys in the U.S., this paper is able to make a simple but fundamental argument: IQ level per se, holding all other personal characteristics constant, has negligible net effect in determining one's income level and thus should not be used as the proper measure of the ability we want to quantify in the wage-determining process, i.e., the very ability to earn income.

I. Introduction

Since the seminal work of Mincer (1958), the relationship between schooling and wage has kept economists fascinated for the past five decades. The conventional wisdom goes that as one becomes more educated, his/her income from work tends to increase. Following this logic, the most instinctive approach to the problem would start by estimating the following equation:

$$W_i = \beta S_i + X_i \alpha + \varepsilon_i$$

where W_i is individual i's income, measured in hourly wage, S_i refers to years of schooling completed, X_i represents a vector of control variables, and ε_i the random error. (Card 1994) This seemingly simple relation has drawn ensuing debates in the past decades over two major issues: the omitted variable bias (OVB) and the endogeneity of schooling. The simplicity of the above equation

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suffers from violation of the very first OLS assumption, i.e., $E(\varepsilon | S) \neq 0$. In the job market signaling model proposed by Michael Spence (1973), more educated individual receives higher income only because education is a signal of higher ability; the correlation between schooling and wage may be the result of an omitted variable, most probably individual ability, which influences both schooling and wage, even though education does not increase one's productivity. Thus, in the past decades, much effort has been devoted to the isolation of the net effect of schooling on wage by inclusion of plausible omitted variables, e.g., individual ability. The second problem concerning the simple set-up is that, as schooling is not randomly assigned across the population, individuals make their own decisions regarding schooling based on a number of different factors (most likely including anticipated income), and thus the problem of endogeneity of schooling arises. Indeed, the mounting debates existing in the literature revolve around the treatment of these two concerns: (1) how to quantify one's ability in separation with other variables; and (2) the choice of instrumental variables to filter schooling. (Griliches 1977)

As much as the above two problems are concerned, much progress has been made in the literature.[1] In recent years, broader topics developed from the initial exploration of returns on human capital have also been extensively studied, with increasing knowledge added to the literature. While interesting issues remain in these two basic directions, this paper makes no attempt to compete in adding to the knowledge of either endogenous schooling decisions or the ability bias symptom. Rather, we notice that so far, there seems to be no paper that has attempted to narrow the focus on examining the ability per se, i.e., an in depth examination of what actually should be interpreted from the ability. With this inquiry, this paper tries to answer a simple but non-negligible question: Does higher IQ really give you higher income?

As a motivation of this paper, we notice that in order to alleviate the apparent OVB problem, various papers have introduced ability as measured by IQ scores, among others, into the wage equation. In Griliches (1976), where he used a two-stage least squares (2SLS) framework to remedy the endogeneity problem, IQ and another measure, scores on the Knowledge of the World of Work (KWW) test, have been used to proxy individual ability. Based on his work, many subsequent studies continue to use similar sets of variables, in which IQ is always used as the endogenous ability measure, [2] to address different issues aroused in the broader direction of returns on human capital. However, such treatment of ability has brought imperfections in virtually any model examining the schooling and wage relation. So what goes wrong? To answer this question, researchers have tried various methods including the inclusion of more potential instruments to further filter the ability measure. Yet, there seems to be little, if

[1] Card (1994) has provided a good summary of the literature concerning these two issues up to his time. More empirical works can be referred but not limited to Harmon and Walker (1995), Callan and Harmon (1999), Rummery, Vella and Verbeek (1999), Denny and Harmon (2000), Trostel, Walker and Woolley (2002). More recent works on models and methods can be referred but not limited to Harmon and Oosterbeek (2000), Dearden and Sianesi (2001), Harmon, Oosterbeek and Walker (2003), Blundell, and Dearden and Sianesi (2005).

[2] In many later works, IQ is used more often as the measure of individual ability than KWW, in which case, KWW is used as an IV to filter the ability factor we want in estimating the wage equation.

any, success in reconciling those counter-intuitive results, e.g., negative ability coefficient[3], inconsistency in the direction of ability bias[4], and so on. Motivated in this regard, this paper proposes a new direction: maybe IQ is indeed useless in the determination of wage. This bold proposal may seem to be fragile, but as we are going to show, level of IQ per se does have little, if any, effects on one's level of expected income, given that the coefficient on IQ in the wage equation is truly unbiased or near unbiased. In other words, the particular Intelligence quotient you possess, holding all other personal characteristics constant, may bear little weight on the determination of your income level, if at all.

To perform our analysis, we proceed as follows: Section II specifies the model we will estimate and justify our use of the generalized method of moments (GMM) rather than standard OLS or otherwise 2SLS as the estimation framework; Section III carries on a discussion on the data we use, the variables concerned, and some limitations to our sample; Section IV presents and discusses our major results obtained; Section V is devoted to a conjecture on the specification of the wage equation inspired by our results in the previous section; Section VI concludes.

II. The Model

To start our analysis, we first specify the functional form of the wage equation we would like to estimate. Without distraction from our purpose, we adopt the typical log wage equation estimated in the literature, which has a convenient form as:

$$LW = \alpha + \beta S + \gamma A + \delta' X + \varepsilon \qquad (1)$$

where LW is the natural logarithm of the wage rate, S is years of schooling completed, A is a measure of ability, X is a vector of other wage determining variables containing experience in years, tenure in years, dummy for residency in the southern states, dummy for residency in metropolitan areas and year dummies,[5] and ε the random error summarizing the effects of other sources of differences in wage rates. This log specification is widely justified by appealing to the well-recognized stylized fact from large cross-sectional data, such as the Current Population Survey in the US, that there exists a linear relationship between log wages and years of schooling.[6] To examine the role of IQ as a measure of the kind of ability we are interested in, i.e., the ability to earn income, we treat IQ as a proxy for the ability in the wage equation and we are indeed interested in estimating the following equation:

$$LW = \beta S + \gamma IQ + \delta' X + \varepsilon \qquad (2)$$

[3] Griliches (1976) and Blackburn and Neumark (1992)
[4] Blackburn and Neumark (1995)
[5] The choice of control variables is subject to debates in the literature. However, to not distract our analysis, we adopt a conservative stance and follow a wide-recognized set of control variables included in the X-vector in the literature, which is similar to Griliches (1976) and Blackburn and Neumark (1992).
[6] See a much more complete discussion in Card (1995).

where the specification is the same as in (1) except that IQ is now in place of A, and we drop the constant α for simplicity, without loss of generality.

Although simple OLS has reduced the OVB problem by the inclusion of many other explanatory variables including ability measured by IQ, errors-in-variables bias arises as the ability may be measured with error, i.e., the IQ measure may be imperfect, which is obviously the case. To see this, we do the following: If η is the measurement error, IQ and ability can be related in the following simple way:

$$IQ = \phi + A + \eta \tag{3}$$

where $E(\eta) = 0$. The interpretation of η as measurement error makes it reasonable to assume that it is uncorrelated with S, A, X and the error term ε in (1). Then, substituting (3) into (1), we obtain:

$$LW = (\alpha - \gamma\phi) + \beta S + \gamma IQ + \delta' X + (\varepsilon - \gamma\eta) \tag{4}$$

It is easy to show that in general, if at least one of the regressors is measured with error, the OLS estimates of all the regression coefficients can be asymptotically biased.[7]

To resolve the above problem, the conventional approach would be the application of 2SLS, as is practiced universally across the literature. Although 2SLS has largely improved the estimation, it relies on the critical assumption that the random errors in the wage equation have the same conditional mean. This homoskedasticity assumption has greatly restricted the generalization of the model and may cause many results to fail in the presence of any robustness tests. To improve estimation, we therefore apply GMM to estimate a hereroskedastic-robust wage equation, which reduces the restrictions on the regression as many as possible. [8] To estimate (2) using GMM, we rewrite (1) into the following form:

$$y_i = z_i'\lambda + \varepsilon_i \tag{5}$$

where $y_i = LW_i$, $z_i' = \begin{pmatrix} 1 & S & A & X \end{pmatrix}$, $\lambda' = \begin{pmatrix} \alpha & \beta & \gamma & \delta' \end{pmatrix}$. Under the efficient GMM assumptions, which we will testify, we would expect the result to be an unbiased wage equation that can allow us to analyze the net effects of respective explanatory variables on wage determination. This asymptotic unbiasedness provides us with some grounds to draw plausible conclusions on any characteristics found in the regressors and their corresponding coefficients, including the purpose of our investigation: is IQ statistically significant in explaining for wage differentials, holding all other personal characteristics constant? In the following, we will first concentrate on estimating (2) using a standard OLS, assuming IQ is an error-free measure. Then we apply GMM to

[7] Because $Cov(IQ,\eta) = E(IQ \cdot \eta) = E[(\phi + A + \eta)\cdot\eta] = Var(\eta)$, it can be shown that $\beta_{OLS} \xrightarrow{p} \beta - \gamma \cdot Var(\eta) \cdot (\Gamma)$ where Γ is a negative term under reasonable conditions concerning the covariance of IQ and schooling. Thus, β_{OLS} is biased upward for schooling.

[8] However, the efficiency of GMM still relies on mainly two assumptions: 1. Instruments are valid. 2. Inner product of the instrument vector and the error term forms a Martingale difference sequence. In empirical applications, one resorts to Hansen's test of over-identifying restriction to test these two assumptions.

estimate the same equation, but allowing for the measurement errors in variables, as well as relaxing the assumption for homoskedasticity in the error term. The GMM approach will entail two distinct treatments of the schooling factor, either predetermined or endogenous. All these results will be analyzed carefully along with the presentation.

III. Discussion on Data, Variables, and Sample Limitations

The data set we use follows the one used in many related papers, typically in Griliches (1976) and later Blackburn and Neumark (1992). The source of data is the first round of the Young Men's Cohort of the National Longitudinal Survey (NLS-Y)[9]. This cohort was first surveyed in 1966 at ages 14-24, with 5,225 respondents, and the same set of young men was resurveyed at one-year intervals thereafter. The sample we used is restricted to non-black males, for several reasons discussed in Blackburn and Neumark (1992).[10] By 1969, about ¼ of the original sample were lost (largely due to high social and spatial mobility) and many others damaged, but records of the 2,026 respondents to the 1969 earnings survey are complete enough to allow for derivation of all the variables concerned. The very reason we want to use this data set is its inclusion of two measures of ability: IQ and KWW, which are the scores from two intelligence tests. The IQ scores were collected as part of a survey of the respondents' schools conducted in 1968. Because of administrative and record-keeping reasons, IQ data are missing for about one third of the sample resulting in only 1,362 individuals with IQ scores available in the year 1969. The KWW test examines respondents' knowledge about the labor market, covering the duties, educational attainment, and relative earnings of ten occupations.[11] The KWW tests were administered as part of the initial survey, and hence are missing very infrequently. Based on the results of Griliches (1976), since KWW cannot be taken as independent of schooling, we describe its relationship to schooling by

$$KWW = \alpha_2 + \beta_2 S + \gamma_2 A + \delta_2 ' X + \varepsilon_2 \tag{6}$$

[9] This data set is by far the most representative and comprehensive source that is accessible for analysis of the issue at hand. It was obtained from surveys on the U.S. civilian non-institutional population of males on a national scale. The repeated observations of the same individuals over time allow us to enhance the time consistency of our results. For more details of the sample, see the data release of the Bureau of Labor Statistics under the U.S. Department of Labor. We use the first round survey data instead of more recent ones because we note in the last section of Griliches' classic paper in 1976 that after assuming for endogeneity of schooling, the behavior of the wage equation becomes not quite consistent with the previous set-up in that paper, one of such inconsistencies being the negative and significant IQ coefficient obtained. Motivated in this regard, we would like to reexamine the relevant data in an attempt to study what had been left over in that paper and other subsequent papers and try to establish any concrete arguments in a new research direction. Future works of the author will reexamine the results obtained in this paper with more recent data in an attempt to reach further conclusions, if possible.

[10] One obvious reason being there were much more data missing for blacks than for whites, making the sample size of complete observations including blacks too small for empirical studies and inferences.

[11] Details are given in Griliches (1976). While the KWW test is seemingly much different from an IQ test, Griliches (1976) found that least squares results for wage equations using IQ or KWW were quite similar.

Given the above equation and the assumption that KWW is orthogonal to the error term in the original wage equation, we introduce KWW as an instrument into the model for alleviation of the errors-in-variables bias illustrated in the previous section. To be more time-consistent, we study wages and their determinants at several points in time: from the year 1966 to the year 1973[12], when that round of survey ended. In this way, we perform the regression using repeated observations of the same individuals over time. The requirements that wages be observed at several points in time, the exclusion of individuals with missing IQ data, the restriction to non-blacks, and other data availability requirements reduce the final sample size to 785. Although the data size has been largely reduced, such a number is still not too small for our purpose. Yet, the refinement of the original sample into this subset invokes potentially three primary sources of selection bias[13], but since they tend not to be directly involved in the problem addressed in this paper, we work fine with the above refined sample.

TABLE I

SUMMARY OF VARIABLES USED

Variable	Abbreviation	Variable
Dependent Variable	LW	Log wage
Independent Variable	S	Completed years of schooling
	IQ	IQ score
	EXPR	Experience of work in years
	TEN	Tenure in years
	RNS	Dummy for residency in the southern states
	SMSA	Dummy for residency in the metropolitan areas
	(Y66,Y67,Y68	Dummy indicating in which year the wage
	Y69,Y70,Y71	rate is observed for an individual
	Y73)	
Instrumental Variable	KWW	Score on the "Knowledge of the World of Work" test
	MRT	Dummy for marital status (1 if married)
	MED	Mother's education in years
	AGE	Age of the individual

The variables in the sample we will make use of in estimating the wage equation (2) are summarized in Table 1 (interpretation of variables are similar to Blackburn and Neumark (1992); their paper also has a detailed discussion of the motivation to choose these variables, which we will not repeat here). For future reference, characteristics of the sample are also summarized in Table 2 (in the year of 1969).

No data set is perfect, and this one has at least two major shortcomings: many data are missing, and the respondents are very young. To deal with the missing data problem, rather than imputing mean value to the missing observations or adding dummies corresponding to each set of missing observations for each of the independent variables (such were what some other researchers in the literature did), we just filter the original sample into a subset

[12] Excluding the year 1972 because the survey data in that particular year were largely missing
[13] For detailed discussion, see Blackburn and Neumark (1992, Section III).

that is neither too large to allow for a complete inclusion of available data, nor too small for a large sample estimation. However, for the second problem, it exists as an endogenous limitation that is hardly reconcilable. We note that in the larger sample that contains 2,026 observations (corresponding to the available data by 1969's earnings survey), the average age is only 22, though the range is from 17 to 27. Concerns are that at such early an age, the full effects of schooling or ability are not easily observable. Even if such effects can be observed with satisfactory accuracy, there are uncertainties of the individual futures to come that are far from a clear picture. Also, much of the labor force behavior of young men in the earlier part of such ages is characterized by search, experimentation, and often a lack of "seriousness."[14] Thus, observations on their encounters with the labor market during these early years cannot be taken as reflecting exhaustively their underlying potential. Given such an inherent constraint, a full picture of the labor market returns to schooling and the relevant issues may be far from reach. Nevertheless, a glimmer of it is there, and that is what we are going to explore here.

TABLE II

SUMMARY OF CHARACTERISTICS OF THE SUBSAMPLE OF YOUNG MEN'S COHORT FROM THE NATIONAL LONGITUDINAL SURVEY (IN THE YEAR OF 1969, N=785) MEANS AND STANDARD DEVIATIONS (IN PARENTHESIS)

COLUMN I		COLUMN II	
Variable	Mean (SD)	Variable	Mean (SD)
RNS...............	0.2692	AGE..................	21.8390
	(0.4438)		(2.9816)
MRT.............	0.5145	S........................	13.4050
	(0.5001)		(2.2318)
SMSA............	0.7045	EXPR................	1.7354
	(0.4566)		(2.1055)
MED.............	10.9103	TEN..................	1.8311
	(2.7411)		(1.6736)
IQ..................	103.8562	LW.....................	5.6867
	(13.6187)		(0.4289)
KWW.............	36.5739		
	(7.3023)		

IV. Major Results

To present and discuss our major results, we first examine the results from a standard OLS approach, laying some grounds for compare and contrast. Then, we devote most part of this section to the examination of regression results in the GMM framework, from which we justify our arguments laid in the very beginning of this paper, and draw our major conclusions.

[14] Pointed out in Griliches (1976), and reemphasized by Gronau (2003).

OLS Estimates

Table 3 summarizes the major results of applying standard OLS to our sample. Findings resemble Griliches (1976), with few distinctions, and here we only identify the ones worth noting related to our analysis:

TABLE III

COEFFICIENTS OF INDEPENDENT VARIABLES IN THE LOG WAGE EQUATION (OLS ESTIMATES, N=785) DEPENDENT VARIABLE: LW

COLUMN I			COLUMN II (Year Dummies)		
Independent Variable	Coefficient (S.E)	t-Statistic (p-Value)	Independent Variable	Coefficient (S.E)	t-Statistic (p-Value)
S	0.0620 (0.0075)	8.2373 (< 0.0001)	year66	4.2354 (0.1211)	34.9839 (< 0.0001)
IQ	0.0027 (0.0011)	2.5205 (0.0117)	year67	4.1811 (0.1242)	33.6549 (< 0.0001)
EXPR	0.0308 (0.0066)	4.7063 (< 0.0001)	year68	4.3159 (0.1242)	34.7487 (< 0.0001)
TEN	0.0422 (0.0071)	5.9007 (< 0.0001)	year69	4.4429 (0.1267)	35.0684 (< 0.0001)
RNS	-0.0963 (0.028)	-3.4375 (0.0006)	year70	4.4636 (0.1368)	32.6211 (< 0.0001)
SMSA	0.1329 (0.0259)	5.1358 (< 0.0001)	year71	4.458 (0.1315)	33.9074 (< 0.0001)
			year73	4.5582 (0.1368)	33.3324 (< 0.0001)

* $R^2 = 0.4301$; instruments are KWW, MRT, MED, and AGE. The coefficients on year dummies are de facto the intercept in the log wage equation given that no intercept term has been specified originally.

1. Note that the coefficients on year dummies are each statistically significant (at 1% level) and more importantly increasing in years (generally), which indicates an increasing trend in the respondents' wages. This finding supports the consistency of intertemporal behavior of the wage equation we specified.
2. β is 0.0620 and is statistically significant (at 1% level). Theoretically, as we have shown, such a coefficient on S should contain an upward bias, under reasonable conditions; the impact of years of schooling completed on wage determination would be overestimated. We note that the "reasonable conditions" are indeed satisfied here given the standard errors estimated for schooling and IQ. One should also note that this coefficient can be interpreted as a measure of the rate of return on schooling, and in this case, the biased marginal return would be 6.2%.

3. γ is 0.0027, which is also statistically significant (at 5% level). The positive coefficient implies a positive returns-to-IQ relation; higher IQ would raise one's wage level, though the magnitude is small, only at a 0.27% level.
4. Note that we differ from the conventional approach (estimate the equation multiple times by including different sets of variables) by only estimating the full version of the wage equation (including all variables specified simultaneously), for the reason that we are only interested in the overall behavior of the key explanatory variables under the OLS framework, which will be used as a reference frame in the following analysis.

GMM Estimates with Predetermined Schooling

Table 4 summarizes the major results from applying GMM to the sample, in the case where schooling is assumed to be predetermined and only IQ is endogenous. The outside instruments are chosen to be KWW, MRT, MED and AGE. In this setting, several interesting findings arise:
1. Note that the coefficients on year dummies are again each very significant (at 1% level) and increasing in years (generally), indicating an increasing trend in the respondents' wages, which again supports the intertemporal consistency of the wage equation behavior.

TABLE IV

COEFFICIENTS OF INDEPENDENT VARIABLES
IN THE LOG WAGE EQUATION
(GMM ESTIMATES, WITH PREDETERMINED SCHOOLING, N=785)
DEPENDENT VARIABLE: LW

COLUMN I			COLUMN II (Year Dummies)		
Independent Variable	Coefficient (S.E)	t-Statistic (p-Value)	Independent Variable	Coefficient (S.E)	t-Statistic (p-Value)
S	0.0768	5.7785	year66	4.4368	15.1248
	(0.0133)	(< 0.0001)		(0.2933)	(< 0.0001)
IQ	-0.0014	-0.3372	year67	4.4158	14.8361
	(0.0042)	(0.7359)		(0.2976)	(< 0.0001)
EXPR	0.0312	4.6419	year68	4.5259	15.6039
	(0.0067)	(< 0.0001)		(0.29)	(< 0.0001)
TEN	0.049	6.6046	year69	4.644	15.4617
	(0.0074)	(< 0.0001)		(0.3004)	(< 0.0001)
RNS	-0.1007	-3.366	year70	4.6706	14.9666
	(0.0299)	(0.0008)		(0.3121)	(< 0.0001)
SMSA	0.1336	5.0245	year71	4.6713	15.2967
	(0.0266)	(< 0.0001)		(0.3054)	(< 0.0001)
			year73	4.7728	15.6015
				(0.3059)	(< 0.0001)

*Instruments are KWW, MRT, MED, and AGE. The coefficients on year dummies are de facto the intercept in the log wage equation given that no intercept term has been specified originally.

2. β is 0.0768 and is statistically significant (at 1% level). If the GMM is indeed efficient (the GMM assumptions hold), such a β should be statistically unbiased, which in other words suggests a downward ability bias rather than an upward bias caused by errors in ability measure under the standard OLS! (though the magnitude of the direction switch is not large) Although the literature has seen debates over the direction of the bias, there is seemingly a wider recognition for the upward potential; thus, the finding here may enhance the evidence of the potential downward bias if the GMM is indeed efficient. Note that previous papers concluding with a downward bias tend to be estimating the wage equation using cross-sectional data only. But in this paper, we exploit the NLS-Y data set's panel feature, though only a tip of the iceberg, to estimate our wage equation with repeated observations of the same individual over time. Hopefully, such a temporal specification would draw stronger evidence on the downward bias of β. Nevertheless, even if the evidence of downward bias is extensive, we should only conclude with care that the direction of bias is confirmed, since the complicated interactions among explanatory variables in the wage equation make any causal relations in the model prone to contamination by the potentially additional OVB problem, errors-in-variables problem and the simultaneous causality problem. In fact, any evidence in this direction is by far only a stepping stone for a more comprehensive anatomy of the causal relation between schooling and wage in the wage equation.

3. When we look at IQ, it is surprising to find that γ in this case is actually negative, -0.0014! (though of only a very small magnitude) However, the negative coefficient might not require further interpretation given that the p value is huge, 0.7359, strongly suggesting a rejection of the null. Thus, the message is clear: under GMM framework, if the instruments are valid enough, we would have an unconventional result that the net effect of IQ on log wage is negligible! However surprising this may sound, we should first check for the critical assumptions underlying efficient GMM, which provide the theoretical grounds for any conclusions.

When we check for the validity of the efficient GMM assumptions, the Hansen's test of over-identifying restriction produces a J statistic of the size 74.1649[15], with a negligible p value. This quickly rejects the tentative conclusion drawn above in part 2, also suggesting a need for reexamination of the direction of bias in part 1; the insignificant IQ coefficient may not suggest anything new but only again a misspecification of the instrumental variables, and the downward ability bias may also be a result of such a misspecification. Although the insignificance of IQ is rejected under the efficient GMM hypothesis, the possible direction of invalidity in ability measure delivers us a strong incentive to look for other possible specifications of the model under which such insignificance proves true.

[15] Empirically, J statistic is never too small, indicating the fact that perfect instruments are mere luxuries. Nevertheless, the convention goes that if the J is not too large, the instruments can be held as reasonably valid up to certain degrees of tolerance of biasedness in the estimated model; in other words, we tolerate the potential biasedness within an appropriate degree and assume validity of the estimated relations in practice. Usually, a J no more than 10 already indicates an acceptable set of instruments.

GMM Estimates with Endogenous Schooling

Induced by the incentive above, we investigate the wage equation under GMM again but with a different specification of a key variable: we assume that schooling is endogenously determined within the wage-determining system. Thus, S and IQ are now both endogenous, with the outside instruments unchanged. Indeed, the problem of endogeneity of schooling has been examined since decades ago in various papers.[16] If one takes the view that the error term includes a host of unobservable individual characteristics that might affect the individual's choice of schooling and quality of schooling, then schooling will be undoubtfully endogenous. Table 5 summarizes the major results:

1. The coefficients on year dummies still exhibit an increasing time trend (generally), with each coefficient value being very significant (at 1% level). This again supports the time-consistent behavior of the specified wage equation. However, one may notice the die down of the trend compared to previous statistics in the last year, which is left unexplained.

TABLE V

COEFFICIENTS OF INDEPENDENT VARIABLES
IN THE LOG WAGE EQUATION
(GMM ESTIMATES, WITH ENDOGENOUS SCHOOLING, N=785)
DEPENDENT VARIABLE: LW

COLUMN I			COLUMN II (Year Dummies)		
Independent Variable	Coefficient (S.E)	t-Statistic (p-Value)	Independent Variable	Coefficient (S.E)	t-Statistic (p-Value)
S	0.1758	8.5021	year66	4.0039	11.9576
	(0.0207)	(< 0.0001)		(0.3348)	(< 0.0001)
IQ	-0.0043	-0.8776	year67	3.9509	11.6251
	(0.0049)	(0.3804)		(0.3399)	(< 0.0001)
EXPR	0.0503	6.2511	year68	4.0499	12.1837
	(0.008)	(< 0.0001)		(0.3324)	(< 0.0001)
TEN	0.0425	4.4973	year69	4.1594	12.0333
	(0.0095)	(< 0.0001)		(0.3457)	(< 0.0001)
RNS	-0.1041	-3.105	year70	4.1709	11.6642
	(0.0335)	(0.0019)		(0.3576)	(< 0.0001)
SMSA	0.1248	4.0537	year71	4.1886	11.6205
	(0.0308)	(0.0001)		(0.3518)	(< 0.0001)
			year73	4.1035	11.5334
				(0.3558)	(< 0.0001)

*Instruments are KWW, MRT, MED, and AGE. The coefficients on year dummies are de facto the intercept in the log wage equation given that no intercept term has been specified originally.

[16] More recent treatments can be referred to Maluccio (1998), Arrazola, De Hevia, Risueno and Sanz (2003), and Klein and Vella (2006).

2. β is 0.1758 and is statistically significant (at 1% level). Again, if the GMM is indeed efficient, such a β should be statistically unbiased, and thus a downward bias is developed for the original OLS estimate rather than an upward bias. Noticeably, if indeed the downward bias is verified, the magnitude would be much larger than in the previous case, i.e., almost triple the value of β ! This suggests a much larger downward bias of β in the standard OLS caused by the errors in ability measure. However, this result is not surprising. Since we now assume for endogeneity of schooling in the wage equation, the simultaneous causality problem would automatically and largely inflate β, if not too much. Empirically, so high a return to schooling is a typical result of the endogeneity problem, reflecting much of the simultaneous impacts of education and income on each other.

3. Compared to the issue of direction and magnitude of ability bias above, which has yet to be confirmed, we are much more interested in exploring the behavior of the ability measure, IQ, under this specification. As expected, γ is indeed again negative, -0.0043, with a larger impact on wage than in the previous case. Yet, given a p value of the size 0.3804, we see again an insignificance of IQ displayed by our sample. However, before any efforts to conclude, we have to first verify the efficient GMM assumptions for a solid theoretical ground.

In this case, Hansen's test of over-identifying restriction produces a J statistic of the size 11.9674, with a much larger p value than under the previous specification. As is discussed earlier, although such a J is still too large for perfect validity of all the efficient assumptions, it is by any means small enough to not reject the instruments as being reasonably acceptable. Empirically, a J statistic of this size already implies quite satisfactory conformity of the model to the efficient GMM assumptions. Given this, we believe that the endogenous schooling specification per se satisfies the efficient GMM reasonably well and thus any inferences we make from the results should not be easily rejected. To see a clearer picture of the fitness to reality of this specification, we perform the C-test on endogeneity of the schooling factor. The C statistic for our sample is 58.1682, with a negligible p value. This tells us the story right away: schooling is indeed endogenous in our sample. In other words, the wage equation with endogenous schooling is indeed a better characterization of the schooling and wage relationship than the one with predetermined schooling. More generally, even though the first GMM specification fails to deliver the solidity of the interesting results obtained, the second specification not only delivers such solidity (in an acceptable way) but also proves to be a better specification per se than the former.

With such evidence at hand, we now go back to address the conjectures made above. Verified as stated, our sample exhibits a downward ability bias. Given the underlying endogeneity of schooling, return to schooling is about 17.58%, which seems empirically exaggerated. Such a high return to schooling can be a typical result of the simultaneous causality problem between schooling and wage, which this paper has not tried to address. In the literature, the mounting concerns of this problem often boil down to one single empirical question: finding a valid instrument uncorrelated with unobserved characteristics but correlated with schooling so as to extract the exogenous schooling component, which is often extremely difficult. However, it is worth noting that recent years have witnessed a methodological advance in microeconometrics and the "Difference-in-Difference" strategy has now been applied to various topics in microeconomics, including the examination of returns-to-schooling. Duflo (2001), among others, has most noticeably applied the strategy to alleviate the problem of endogeneity and estimated a net effect of returns-to-schooling of the size 7.2%, which is an encouraging finding to most people. Though we recognize the importance to understand more in this research direction, we restrict our focus on the discussion of ability measure in this paper.

One may find it intriguing to have observed a statistically insignificant IQ factor in the wage-determining system, after confirming the endogeneity of schooling. It may be surprising to the majority that one's IQ level per se has little, if at all, impact on his/her wage outcome. This may sound counter-intuitive: even if you are smarter than others, you may not earn as much as he/she does, let alone strictly more. However, one should note a critical qualification here that the result from our sample does not assert absolutely zero role of IQ in the wage equation unconditionally, but rather that the particular intelligence quotient you possess (the general individual cognitive ability), holding all other personal characteristics constant, may bear little weight on the determination of your income level, if at all. Inspired by several critical works in the fields of psychology, social behavior and mental science [17], we argue that the insignificance of IQ found in our sample should not be referred to as a denial of any effects on income from individual ability in general, but should be interpreted as an indication of the fact that IQ is not a good measure at all of the ability we want to include in the wage equation, more specifically, the very ability to earn income.[18] We believe that individual ability in general can be decomposed into several more specific components, each of which corresponds to a particular aspect of human life. Intelligence quotient, or more accurately the cognitive aspects of one's mental functions such as memory and problem-solving, may be a good measure of one's ability to score in examinations or achieve in academics, but not necessarily a good one of his/her mental ability to socialize, to work, or to simply survive (though IQ may have some effects on wage possibly through its influence on other components of the individual ability or other personal characteristics like the types of jobs engaged; in this case, the effects are not what we are talking about, i.e., the net effect of IQ per se). So under the efficient GMM setting, with largely eliminated bias in γ, the net effect of IQ on wage should be negligible. If we believe in this story, it becomes natural that one would get an insignificant result of IQ in the wage equation we specified, and the reason is simple: you are using the wrong measurement to measure the wage-earning ability.

[17] Cote and Miners (2006), Petrides, Frederickson, and Furnham (2004), and Gardner (1983), among others

[18] Equation (3) actually allows for the possibility that IQ may not be an error-free measure of the relevant ability concept, but the empirical results obtained in this section suggest that the specified wage equation simply captures little of the realistic relationship between the ability we want to quantify and the most accessible measure we have—IQ. In other words, it is not that ability is measured with error by IQ, but that IQ simply should not be included in the equation as the measure of such ability at all.

Other than the major results above, one more issue is worth noting: the negative IQ coefficient γ. Although a simple t-test suggests IQ is statistically insignificant in both predetermined and endogenous schooling settings, the consistent results of a negative sign are still too interesting to ignore. Put aside the testing results, if we assume a negative γ to be accepted, then our sample simply says that with all others equal, a higher IQ level per se will give you a lower level of expected income. This is pathetic! However, it may sound empirically stupid to conclude with such a remark as higher IQ reduces your income. Therefore, what went wrong? Although this paper has not tried to explore the possibilities in this regard, we conjecture that a closer look at the data may provide some clues, e.g., a comparison of subsamples of young men with different education levels within the 785-observation sample to examine the conditional effects of IQ on wage and test the difference in means to verify any possible group bias in the data.

V. Conjecture on the Wage Equation

Following the logic from last section, it is believed that although IQ may be a good measure of one's cognitive ability, it may not necessarily be a good proxy for the more specific component of ability that we are interested in—the very ability to earn income. So the problem now boils down to two questions: 1) What kind of individual ability should we include in the wage equation instead of IQ (or with IQ)? and 2) What should a better specification of the wage-determining system be?

Schooling and IQ

Before we try to answer these two questions, we carry on a short discussion on IQ in addition to the previous section. Note that in the standard OLS regression, the biasedness of slope coefficients allows for a positive and significant γ. Given the results from efficient GMM, such a γ cannot be a reflection of the net ability impact on wage but only a result of some unknown internal invalidities of the wage equation. Given this, one might naturally suspect a typical multicollinearity problem in schooling and IQ, which may take the form:

$$S = \kappa + \rho IQ + u \tag{7}$$

Based on the sample of 785 observations we used, we obtain an R^2 of the size 0.4667. The F-test on this R^2 produces an F statistic of the size 54.3205, which suggests a very strong linear relationship between schooling and IQ, confirming the multicollinearity concern. Given such severe multicollinearity, the standard OLS would easily produce a statistically significant marginal impact of IQ on wage, which in this case should be understood as the "impact IQ has on wage through schooling attainment". This is intuitive: even though IQ is not a good measure of the ability to earn income, it would be a reasonably good one to measure the intelligence one possesses in terms of passing exams and doing well in course work. Therefore, even though IQ per se has little effect on wages, we would expect a statistically significant impact of IQ on wage in an OLS set-up through its positive correlation with schooling and schooling's positive correlation with wage. This attends to our previous argument: even though IQ has a positive impact on wage in an OLS regression, once we apply the efficient GMM and reduce estimation bias as much as possible, the net effect of IQ on wage is negligible. The result here also echoes the remark made earlier: although the net effect of IQ may be negligible, the presence of IQ differentials may still influence the wage-determining behavior of the wage equation, through its relations with education attainment, other individual ability components, or some personal characteristics like the types of jobs engaged. Consequently, a complete exclusion of the IQ component from the wage equation may shut down many possible channels, which would not be a wise choice after all. Typically, we can characterize the observed correlation between schooling and IQ by the following equation:

$$S = \gamma_3 IQ + \delta_3 ' X + \varepsilon_3 \tag{8}$$

where X is again a vector of control variables allowing for other possible factors that have a correlation with schooling.

Emotional Intelligence

Now we attempt to explore the two questions posed at the beginning of this section. To identify an appropriate measure for the specific ability to earn income, one may be more concerned with an individual's ability to fit into the work place, on top of satisfactory task completion. Indeed, even if one possesses high IQ, he/she may not be able to realize his/her personal value and earn the return he/she desires if he/she cannot fit into the work place, cooperate with colleagues, and maintain good self-discipline. Extensive evidence[19] from the fields of intelligence studies, social psychology and organizational behavior has pointed towards the same empirical fact that non-cognitive ability, such as self control, empathy, and interpersonal relation management, could play a far more dominant role than IQ in the determination of not only one's income from work but also his/her career prospects and professional development, and even the success of an organization. In 1983, Howard Gardner's *Frames of Mind: The Theory of Multiple Intelligences* introduced the idea of multiple intelligences, which include both "interpersonal intelligence" (the capacity to understand the intentions, motivations and desires of other people) and "intrapersonal intelligence" (the capacity to understand oneself, to appreciate one's feelings, fears and motivations) besides IQ. In Gardner's view, traditional types of intelligence, such as IQ, fail to fully explain one's mental abilities. In the recent decade, the above ideas have been popularized in the academia as well as in the workplace through the introduction and diffusion of a collective measure of non-cognitive ability, the emotional intelligence (EI)[20]. Increasing recent evidence has shown that EI may be a better measure of workplace ability than IQ and is usually more relevant to job performance. (Jayan 2006, Cote and Miners 2006, and Law, Wong, and Huang 2008) Most noticeably, the results of Cote and Miners (2006) conclude

[19] Such evidence can be found in the following works: Thorndike, E. L. (1920), Wechsler, David (1940), Mayer, J.D. and Salovey, P. (1997), Weisinger, H. (1998), Fox, S. and Spector, P.E. (2000), Daus, C.S. and Ashkanasy, N.M. (2005), Lyons, J.B. and Schneider, T.R. (2005).

[20] Emotional intelligence describes the ability, capacity, skill or, in the case of the trait EI model, a self-perceived grand ability to identify, assess, manage and control the emotions of one's self, of others, and of groups (Bradberry and Greaves, 2009). Several standard tests have been developed so far to quantify the subject, among which the Mayer-Salovey-Caruso EI Test is the most popular.

with the observation that employees with higher EI tend to have higher task performance and organizational citizenship, and thus their compensations, even if they are the ones with lower IQ. Motivated in this regard, we are interested in exploring the possibilities of EI being a better measure of the ability to earn income. In other words, we conjecture that EI could be a statistically significant explanatory variable originally omitted in the wage equation, the inclusion of which may reasonably improve the model's fit to reality and allow us to have a more accurate estimation about the net marginal contribution to wage from an individual's relevant wage-earning ability.

Augmented Wage Equation

Given the analysis above, we proceed to offer our conjecture on a better functional form of the critical log wage equation. Since we have shown the necessity of inclusion of IQ albeit the insignificance of its net effect, and realized that EI may be a better measure of the ability to earn income, we augment the equation to include both IQ and EI as explanatory variables:

$$LW = \beta S + \gamma_I IQ + \gamma_E EI + \delta' X + \varepsilon \tag{9}$$

And in order to give a closed form specification of the wage equation, we define the general ability A by the following equation, which include the wage-earning ability measure EI, the cognitive ability measure IQ, and the outside ability measure KWW serving as an instrument in GMM estimates:

$$A = b_0 + b_1 IQ + b_2 EI + b_3 KWW + e \tag{10}$$

In addition to the closed form requirement, in order to reveal the inherent relation between IQ and EI, we should as well specify the exact functional form of the relation. This allows us to examine any cross effects of the two terms in the augmented equation, making it possible to analyze the interactions of one's different aspects of ability in a tractable form. In fact, there are many models in the literature of intelligence studies concerning the exact categorization of human intelligence, but as we prefer to limit the purpose of this paper, we will not extend our discussions to include further issues in detail but would leave the task of finding an appropriate functional form of the relation to future research, while only indicate such a requirement by the following implicit function:

$$f(IQ, EI) = 0 \tag{11}$$

Given such modified specifications, equations (8)-(11) constitute a new system of wage determination that can be studied in a tractable way and estimated in both structural and reduced form. In this case, one can either 1) drop EI to obtain the original wage equation specified for analysis in the previous sections so as to verify for the "insignificance of IQ" conclusion; or 2) drop IQ to obtain an estimate of the net effect of EI on wage, to examine the statistic significance of such an ability measure in wage determination, to verify the assumption that EI is a better measure of the wage-earning ability, to analyze the directions and magnitudes of the marginal impacts of all other explanatory variables, and to possibly identify any potentially additional biases introduced into the wage equation by the inclusion of EI; or 3) estimate the equation in the presence of both IQ and EI simultaneously, to reexamine EI about the issues raised in 2) in the presence of an endogenous IQ, to identify any possible new channels through which IQ can affect wage after the inclusion of EI, to examine the cross effects, if any, between EI and IQ so as to understand better the interactions among different aspects of individual ability, to test the endogeneity of schooling assumption again under this set-up, and to examine the overall fitness of this specification to the reality. [21]

VI. Conclusion

This paper builds on the progress of several classic studies of returns-to-schooling, but asks a different question from the traditional inquiries, in the direction of ability measure per se, i.e., what should be interpreted from the individual ability in the wage equation? Motivated by several historically important issues in the area, we answer this question by taking a very simple stance: IQ level per se has negligible effect in determining one's income level as measured by hourly wage. We utilized a sample of well documented national surveys on young men' cohort in the U.S. between 1960s and 1970s to perform an empirical study of the problem concerned: whether IQ is statistically significant in the estimation. We analyze the data under three frameworks (OLS, GMM with predetermined schooling and GMM with endogenous schooling) to compare and contrast, and derive our major results in Section IV, including the central result that confirms the insignificance of net IQ effect in the wage-determining system. We have also drawn some other interesting conclusions and implications from the empirical results obtained, including the direction of ability bias, time consistency of wage-earning behavior, endogeneity of schooling decisions, possibly negative marginal impact of IQ, and the multicollinearity in IQ and schooling. In order to provide possible directions for future research, we have also made a conjecture on the wage equation (the wage-determining system) towards the end of this paper and propose emotional intelligence as a better wage-earning ability measure to coexist with IQ in an augmented wage equation to enrich the interactive effects and dynamic behavior of the wage-determining process. We hope that the proposal can be implemented in future studies and the conjecture be tested with empirical data, which is our work that ensues.

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[21] Although we have proposed a new form of wage equation specification, the purpose of this paper has already been reached and we prefer not to struggle with any attempts on the issues raised but leave them to future research.

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