An Empirical Analysis of the Risk Properties of Human Capital Returns

By Ignacio Palacios-Huerta*

Human capital resources are a crucial part of an individual's capital holdings and comprise much of the total aggregate wealth in the United States and other economically advanced nations. During the last few decades, much energy has been devoted to the analysis of human capital and its empirical regularities. The result has been the accumulation of a large amount of evidence supporting the importance of human capital to the structure and evolution of earnings, occupations, employment and unemployment, fertility, and economic growth and development.[1]

Only relatively recently, however, have economists begun to undertake a systematic analysis of the properties of investment returns and their implications for models of dynamic economies. Much of this analysis has been concerned with the analysis of risky and riskless financial assets, and their implications for intertemporal models of consumer optimization. Although considerable progress has been made in the recent literature toward understanding the properties and implications of investment returns, and although human capital assets are the main form of individual and aggregate investments, this progress has not reached the human capital literature. As a result, a number of crucial questions remain unanswered. For instance, consider the issues raised by Gary S. Becker (1993, p. 205):

> This chapter adds several dimensions to the evaluation of the effects of college education on earnings and productivity by *comparing* private and social gains from college education with those of *other investments.* These comparisons permit a determination of how much is *gained or lost by individuals and society* from investment in the former rather than in the latter, and are essential to determine whether there is underinvestment in college education; they also *help* determine whether capital market difficulties, the lack of knowledge and liquidity, etc., ... have serious impediments to the flow of resources into college education (italics added).

These arguments apply not only to college and high school education but to any education level or other forms of human capital. A suitable comparison of the properties of different risky human capital returns, and of human capital and financial returns, can then provide crucial information about these key matters. These comparisons, which also are of great relevance to public policy, represent the subject matter of the analysis in this paper.

Interestingly, there is relatively little research in the literature that helps us understand how the risk-return trade-off for different human capital investments and for financial investments may compare at the margin. Moreover, the approach adopted in the literature is unsatisfactory and generally invalid. The procedure usually followed is to compare *average* levels of human

* Department of Economics, Brown University, Box B, Providence, RI 02912 (e-mail: ipalacios@brown.edu). I owe a debt of deep gratitude to Gary S. Becker, Kevin M. Murphy, and Guillermo Mondino for their helpful comments on earlier drafts, encouragement, and several stimulating discussions. I also benefited from conversations with Moshe Buchinsky, John Cochrane, Andrew Foster, Lars Hansen, Kenneth Judd, Paul Romer, Sherwin Rosen, Stanley Zin, from the suggestions of two anonymous referees, and from the audiences at seminars held at the University of Chicago, Stanford University, Brown University, the University of Cambridge, London Business School, the Amos Tuck School of Business, and the University of Miami. I am especially thankful to Giorgio De Santis for his programming assistance, to the National Fellows Program at the Hoover Institution and the George J. Stigler Center at the University of Chicago for their hospitality and financial support, and to Surrey Walton for research assistance. Any errors are mine alone.

[1] Sherwin H. Rosen (1987) reviews the human capital literature and its impact up to the last decade. Dale W. Jorgenson and Barbara Fraumeni (1989) estimate that the share of human capital wealth in the aggregate wealth of the United States during 1948–1989 was around a remarkable 93 percent. At the aggregate level, labor receives at least two-thirds of total income in the United States and other economically advanced nations.

capital rates of return, ignoring the role of risk, and restricting the intertemporal marginal rate of substitution (IMRS) of the consumer to a particular function of observed data. The first aspect is pointed out in Becker (1993, p. 4) who, with regard to his own influential book, says:

> There is a more serious *error* in my discussion of the *riskiness of investments in education.* I ignored the then developing literature on optimal portfolios, and did not derive my measure of marginal risk—the variance in the rate of return—from an analysis of utility maximization (italics added).

Unfortunately, this error has never been corrected in the human capital literature. Moreover, no analysis has even attempted to compare the risk-return properties of different human capital assets. Therefore, no reliable estimates of investment gains or losses by individuals and society exists.

The purpose of this paper is to begin to fill this gap by providing an empirical comparison of the properties of risk-adjusted human capital rates of return. As Becker remarks, the principal challenge is to incorporate the role of riskiness of investments in education into the comparison of investment returns: How can marginal risk be derived from utility maximization? How then can returns, or returns relative to their variability, be compared? A second challenge is to avoid restricting the IMRS of the consumer to a specific function of the observed data. As in most investment models, a common implication of human capital investment models is that the equilibrium price of future human capital payoffs can be represented as the expectation, conditioned on current information, of the product of the payoff and the IMRS of the consumer. The exclusive approach taken in the human capital literature is to restrict the IMRS to be a specific parametric function of the observed data. This restriction leads to a number of difficulties, the main one being that the results of the empirical estimations depend on the particular features assumed about the utility function.[2]

The analysis in this paper overcomes these two important impediments by exploiting the properties of some recently developed methodologies for the analysis of asset returns and intertemporal utility-based models. In particular, in recent years the finance literature has witnessed an increasing use of tests for mean-variance spanning, as first introduced by Gur Huberman and Shmuel Kandel (1987). The literature on mean-variance spanning analyzes the effects that the introduction of additional assets has on the mean-variance frontier of certain benchmark assets. There is mean-variance spanning if the frontier of the benchmark assets alone coincides with the frontier of the benchmark assets plus the new assets. For instance, consider an individual investing in human capital. If the frontier associated with his human capital assets alone coincides with the frontier of the human capital assets plus a financial asset, then mean-variance spanning means that the individual will not be able to improve upon his human capital investment by investing in the financial asset. If the frontiers do not coincide, then the mean-variance characteristics of his original investment could be enhanced by also investing in the financial asset. Empirically, it is important to note that recent research shows that labor income risk represents an important pervasive risk factor at the aggregate level that requires a substantial risk premium in financial markets.[3] Similarly, we can examine the *properties* of different human capital returns by examining the differences in the mean-variance frontiers that they span when a new human capital asset is introduced.

As Giorgio De Santis (1993) and other authors have shown, the hypothesis of mean-variance spanning can be formulated in terms of the volatility bounds on the IMRS introduced by

[2] John C. Hause (1974) in his critique of Yoram Weiss (1972) already points out the problems with calculations based on arbitrary utility functions and the importance of characterizing classes of utility functions suitable for analyzing the uncertainty and risk elements in human capital markets.

[3] See John Y. Campbell (1996), Ravi Jagannathan and Zhenyu Wang (1996), and Jagannathan et al. (1998). These papers, however, do not examine the incremental contribution to risk and return from investing in financial assets from the perspective of someone who owns human capital or vice versa. Previous to these papers, Eugene F. Fama and G. William Schwert (1977) examined the Capital Asset Pricing Model (CAPM) with the nonmarketable income model of David Mayers (1972) using the growth rate in per capita labor income.

Lars P. Hansen and Jagannathan (1991), and extended in Hansen et al. (1995), without restricting the IMRS to be any specific parametric function of the observed data. Frans A. De Roon and Theo E. Nijman (2001), who offer a thorough review of the literature on mean-variance spanning, describe in detail the duality between mean-variance frontiers and volatility bounds. In this paper we study the risk properties of human capital returns both in terms of mean-variance frontiers using the test introduced by Huberman and Kandel (1987) and in terms of volatility bounds on the IMRS using De Santis' (1993) procedure.

It is important to remark that these methodologies for comparing the properties of investment returns allow us to overcome existing shortcomings in the human capital literature since: (i) the measure of marginal risk may be derived from an analysis of utility maximization; (ii) differences in marginal risk and returns can be accounted for by estimating differences in mean-variance frontiers using the covariance structure of returns; and (iii) no particular form of the utility function needs to be specified and, as a result, risk-return differentials do not depend on the form of the utility function and the degree of risk aversion.

In what follows we will examine the properties of human capital returns at the level of aggregation of demographic groups characterized by sex, race, education, and experience. The empirical analysis yields a number of results. First, we can determine the size of the gain or loss associated with different forms of risky human capital investments and financial investments for the different demographic groups. For the period 1964–1996, we find that the gains from a college (or greater) education per unit of risk are from 5 percent to more than 20 percent greater than from risky financial assets, whereas the losses from a high school (or lower) education per unit of risk relative to risky financial assets are typically greater than 15 percent for most demographic groups. Second, as Becker remarks, these comparisons also help to determine how serious human capital market difficulties, lack of knowledge, and liquidity problems may be. In particular, we can separate two different sources of gains and losses from investments. On the one hand, differences between human capital and financial assets in terms of returns per unit of risk may be attributed to differences in the nature and markets of these assets (e.g., liquidity, taxation). On the other hand, differences across demographic groups (sex and race) for given human capital holdings (e.g., a college education) will be associated with *relative* differences in nonmonetary returns, capital market difficulties, frictions, and other circumstances across these demographic groups. We often find substantial differences across some sex and race groups with identical human capital holdings.

I. Measures of Human Capital Returns

The measurement of human capital returns has been subject to a great deal of attention in the literature. David Card (2001) offers a comprehensive review of the literature, as well as an extended discussion of various econometric issues. Given the various procedures available in the literature for estimating the returns to schooling, we will evaluate the robustness of the empirical findings for various measures of human capital returns. The basic measure we consider can be described as follows. Returns to schooling are typically calculated as the proportional increase in earnings per year associated with the last unit of education (the marginal return). Thus, we shall consider the marginal payoff of the last unit of education over one period, from t to $t+1$. Let $w_{e,t}$ denote the real payoff at time t of an individual with e units of education. The marginal return can then be approximated as:

$$R^h_{e,t+1} = \frac{w_{e,t+1}}{w_{e-1,t}}. \tag{1}$$

This approximation accounts for both the one-period gains obtained from owning $e-1$ units of human capital at t, as well as the skill premium from owning one more unit at a given time. To see this, note that it can be decomposed as:

$$\begin{aligned} R^h_{e,t+1} &= \frac{w_{e-1,t+1}}{w_{e-1,t}} \cdot \frac{w_{e,t+1}}{w_{e-1,t+1}} \\ &= r^{e-1}_{t,t+1} \cdot r^{t+1}_{e-1,e}. \end{aligned} \tag{2}$$

The first fraction captures the gains associated with $e-1$ units of education. These gains, which on average are around 2 percent per year, are typically ignored or, at best, indirectly approximated in other human capital measures (Card, 2001). The second fraction captures the relative extra wages that are obtained by owning one more unit of education at a given time. In this sense, the measure $R^h_{e,t+1}$ captures the trade-off associated with the marginal productivities of different levels of education ($e - 1$ and e) over one period of time, as it captures the earnings premium obtained at $t + 1$ relative to t obtained from one more unit of education.[4] Alternatively, this measure may be interpreted as the premium necessary to transfer a given individual from his current life-cycle wage profile to that of someone with one more unit of education from t to $t + 1$ when forgone wages represent the cost of schooling.

The empirical tests will be implemented using wages to construct this measure for the different demographic groups, and will be extended to account for tuition fees, as well as for the effects of ability and selectivity biases in the measurement of wages. In addition, we will consider the traditional Becker-Mincer approach to estimate human capital returns, the measure suggested in the endogenous labor supply model of Moshe Buchinsky and Philip Leslie (1997), and the growth rate in labor income accounting for the effects of revisions in future labor income and discount rates suggested in Campbell (1996).[5] In anticipation of the results, it is important to remark that we will find extremely similar results across the different measures.

II. Mean-Variance Spanning Methodology

The typical optimization problem of an individual consists of choosing the consumption and investments that maximize his expected lifetime discounted utility $\sum_{t=0}^{\infty} \beta^t E_t u(c_t)$, where $u(\cdot)$ is a well-behaved utility function, $E_t[\,\cdot\,]$ denotes the expectation conditional on information available at time t, $\beta > 0$ represents the rate of time preference, and c_t is consumption at date t. Let $R^i_{t+1} = 1 + r^i_{t+1}$, $i = 1, \ldots, n$, denote the real return of asset i from date t to date $t + 1$, $\mathbf{R}_{t+1}$ the n-dimensional vector of these returns, and R^f_{t+1} the real return earned by a riskless asset. The equilibrium conditions in these models are:

$$E_t[m_{t+1}\mathbf{R}_{t+1}] \leq \mathbf{1}, \tag{3}$$

$$E_t[m_{t+1}R^f_{t+1}] \leq 1,$$

where the IMRS is $m_{t+1} = \beta u'(c_{t+1})/u'(c_t)$ and $R^f_{t+1} = \frac{1}{E_t[m_{t+1}]}$.[6] These conditions hold with equality if there are no market frictions and with inequality otherwise.[7] More generally, define R^e_{t+1} as the difference between any two asset returns. Then, the equilibrium conditions can be written as $E_t(m_{t+1}R^e_{t+1}) = 0$, which implies that

$$\frac{\sigma(m)}{E(m)} \geq \frac{|E(R^e)|}{\sigma(R^e)}. \tag{4}$$

[4] I am indebted to Kevin M. Murphy for suggesting this approximation. This measure can also be interpreted as the gross income less the maintenance costs that must be incurred to keep a unit of human capital in working order (see Becker, 1971). Note also that if we define $w_{t+j,e} = w_{t+j,e-1} + d_{t+j,e}$, then the usual present value expression of the typical human capital investment model is obtained: $w_{t,e-1} \leq E_t \sum_{j=1}^{\infty} \beta^j [u'(c_{t+j})/u'(c_t)] d_{t+j,e}$, and $\lim_{j\to\infty} \beta^j u'(c_{t+j}) w_{t+j,e} = 0$. This expression indicates that utils provided by net real wages today (t) with education $e - 1$, are equal to the expected discounted sum of utils provided by the additional wages $d_{t+j,e}$ (wages with education e minus wages with education $e - 1$) that one more unit of education will provide in the future. This measure is also useful to help explain the size of the international diversification puzzle when human capital is considered part of the wealth portfolio of individuals (Palacios-Huerta, 2001a).

[5] Relative to Campbell's (1996) measure, $R^h_{e,t+1}$ adjusts the growth rate of real wages for a *given* education level $r^{e-1}_{t,t+1}$ by the education premium term $r^{t+1}_{e-1,e}$, which is typically important and sizable, but does not include the effects of revision in future labor income and discount rates. Fama and Schwert (1977) and Jagannathan and Wang (1996) consider only the growth rate in per capita labor income, which is the stationary analogue of the per capita labor income variable used in Mayers' (1972) one-period model.

[6] In utility-based models, m is simply the IMRS of the consumer. This discount factor can be parametrized in several ways leading to the typical models used in the finance literature, e.g., the CAPM and factor models such as the Arbitrage Pricing Theory (APT) and the Chen-Roll-Ross model. No specific parametrization needs to be assumed here. As a result, the implications are as general as possible.

[7] See Hua He and David M. Modest (1995) and Erzo G. J. Luttmer (1996) for the equilibrium Euler inequalities for the cases of short-sale constraints, borrowing constraints, solvency constraints, and proportional transaction costs.

This means that the lower bound on the standard deviation of the IMRS is determined by the familiar mean-variance frontier for asset returns from the asset with the greatest Sharpe ratio. Hansen and Jagannathan (1991) show how this duality between the frontiers for the IMRS and for asset returns allows us both to construct minimum variance random variables m^{v} from the set of returns and to analyze the mean-variance implications of investment returns. In particular, we are interested in comparing the properties of the human capital returns of two different demographic groups, as well as the properties of the human capital returns of a given demographic group with those of financial returns.

In general, these comparisons can be implemented following an intuitive procedure which can be described as follows. Let $\mathbf{R}_A$ and $\mathbf{R}_B$ denote two different vectors of asset returns. Consider the variables $m_A = \mathbf{R}'_A \cdot \boldsymbol{\gamma}'_A$, $m_B = \mathbf{R}'_B \cdot \boldsymbol{\gamma}'_B$, and the variable $m = \mathbf{R}' \cdot \boldsymbol{\beta}' = [\mathbf{R}'_A \ \ \mathbf{R}'_B] \cdot [\boldsymbol{\beta}_A \ \ \boldsymbol{\beta}_B]'$, for given risk-free rate $R^f_{t+1} = v$.[8] We want to examine the effects of adding the vector $\mathbf{R}_B$ to the benchmark set of returns $\mathbf{R}_A$ and vice versa. That is, we consider the comparison between $\mathbf{R}_i$ and R for both $i = A, B$. Following the procedure in De Santis (1993), it is then possible to develop a test of over-identifying restrictions to evaluate the hypothesis of coincidence of the mean-variance frontier associated with $\mathbf{R}_i$ and the frontier associated with $\mathbf{R}$, for $i = A, B$. The test is equivalent to a test of the coincidence of the volatility bounds on m_i and the bounds on m, for $i = A, B$. Under the null hypothesis that the returns $\mathbf{R}_A$ and $\mathbf{R}_B$ have the same stochastic properties, then $\mathbf{R}_i$ spans $\mathbf{R}$, for both $i = A, B$. In terms of volatility bounds on the IMRS, the hypothesis of mean-variance spanning means that a comparison between m_i and m will yield that the $\boldsymbol{\beta}_j$ coefficients, $i \neq j$, in the vector $\boldsymbol{\beta} = [\boldsymbol{\beta}_A \ \ \boldsymbol{\beta}_B]$ are zero; that is, that the volatility bounds on the IMRS implied by $\mathbf{R}_i$ and $\mathbf{R}$ are statistically identical.

In our empirical analysis we evaluate risk-adjusted differences in rates of return following two different methodologies. First we consider De Santis' (1993) χ^2 test of comparison of frontiers. This test uses the covariance structure of returns in measuring the extent of risk-return differentials across different sets of investment returns, and is implemented using the General Method of Moments (GMM). Second, as indicated earlier, we also test the hypotheses of mean-variance spanning using the test developed in the seminal paper of Huberman and Kandel (1987). These authors propose a likelihood ratio test. Although this test involves additional restrictions, the exact distribution of the test statistic under the null hypothesis is known.[9] A comparison of the small sample properties of these and other test procedures can be found in Geert Beckaert and Michael S. Urias (1996). The small sample results suggest that the likelihood ratio test for spanning proposed by Huberman and Kandel (1987) has better power properties than the GMM-based tests in the literature. A detailed description of the tests can be found in the survey on testing methodologies for mean-variance spanning by De Roon and Nijman (2001).

Lastly, in addition to evaluating whether the change in frontiers is statistically significant using these two testing procedures, it is also important to measure *how much* the frontiers change when the different human capital and financial returns are compared. We will consider the distance between the frontiers at the value of $E(m)$ that corresponds to the minimum of the frontier of m. This statistic is equal to the change in the Sharpe ratio divided by the risk-free return that corresponds to that value of $E(m)$. Since the minimum is typically very close to one, the change in the frontiers is ap-

[8] Hansen and Jagannathan (1991) show that the stochastic discount factor $m^{v} = \mathbf{R}^{v\prime} \boldsymbol{\beta}^{v\prime} = [\mathbf{R}'_A \ \mathbf{R}'_B \ 1/v][\boldsymbol{\beta}_A \ \ \boldsymbol{\beta}_B \ \ \varphi]' = \mathbf{R}^{v\prime}[E(\mathbf{R}^{v}\mathbf{R}^{v\prime})]^{-1}\mathbf{1}$ has the same mean as the true m, and has the minimum variance among all the possible variables that satisfy $E_t[m_{t+1}\mathbf{R}_{t+1}] = \mathbf{1}$. This random variable can be evaluated from the vector of asset returns as long as $E(\mathbf{R}^{v}\mathbf{R}^{v\prime})$ is nonsingular. They also show that all feasible m must obey $\sigma(m) \geq \boldsymbol{\beta}'\boldsymbol{\Sigma}\boldsymbol{\beta}$, where $\boldsymbol{\Sigma}$ is the variance-covariance matrix of the risky asset returns.

[9] Huberman and Kandel (1987) show how the regression methodology can be used to test the hypothesis of mean-variance spanning. Their hypothesis of spanning means that each return of the assets that are added to a benchmark set of assets can be written as the return on the portfolio of the benchmark assets plus an error term. The test, therefore, involves linear restrictions on the regression coefficients. Clearly, under the null hypothesis of spanning, since such an additional asset can only add to the variance of the original portfolio, individuals would not like to include them in their portfolio.

proximately equal to the increase in the expected return per unit of risk that is obtained when additional returns are included in the original set:

$$(5) \qquad \Delta\sigma(m) \geq \Delta\left[\frac{|E(R^e)|}{\sigma(R^e)}\right] \cdot E(m)$$

$$= \Delta\left[\frac{|E(R^e)|}{\sigma(R^e)}\right] \cdot \frac{1}{R^f_{t+1}}.$$

In concluding this brief description of the testing methodology, it is important to remark the following aspects:

First, the methodology allows us to compare the stochastic *properties* of different human capital and financial returns accounting for risk, without imposing or assuming that a specific parametric model for the IMRS is generating the returns.

Second, it is possible to take explicit account of the differential riskiness of investments in education by using the covariance structure of returns in measuring differences in mean-variance frontiers.

Lastly, the comparison of risk-adjusted rates of return across different human capital assets and financial assets does not and cannot test for *specific* frictions in human capital markets. This would require testing whether specific m's and specific Euler inequalities are consistent with human capital returns under different specifications of preferences.[10] This is likely the reason why Becker (1993) considers that these comparisons *help* determining whether capital market difficulties, the lack of knowledge, liquidity problems, or other frictions, may impede the flow of resources into education.[11] For instance, if human capital assets were as liquid as financial assets and if they were subject to identical taxation, lack of arbitrage opportunities would imply that they span the *same* return space. Any differences in mean-variance frontiers that we may find will then indicate the gains and losses associated with differences in the nature of these assets, their markets, frictions, and taxation. Likewise, differences in mean-variance frontiers across demographic groups with identical human capital assets (e.g., a college education) will be associated with differences in frictions, circumstances, nonmonetary gains, or market structures where the different individuals operate.[12] The comparisons we implement in the next section, therefore, may be interpreted in this sense.

III. Data and Empirical Evidence

A. *Data*

Yearly data on the U.S. equity index and the U.S. Treasury bill for the period March 1963–March 1996 were obtained from the Center for Research in Security Prices (CRSP) files. Equity returns include both capital gains and dividend yields. The wage data come from the March Current Population Survey (CPS) for survey years 1964 to 1996. The CPS provides information on earnings and weeks worked in the calendar year preceding the March survey, for approximately 1.4 million workers. The data are initially divided into 2,880 distinct groups, distinguished by sex, race (white, black), years of education (1 to 18), and potential years of experience (from 0 to 40), defined as $\min\{age - years\ of\ schooling - 7, age - 17\}$. The average real weekly wage of full-time workers is then computed within each gender-race-education-experience cell as total annual earnings deflated by the personal consumption expenditure deflator from the national income and product accounts divided by total weeks worked.[13] We test the properties of human capital returns at this level of aggregation.

[10] See Palacios-Huerta (2001b) for an analysis of the extent to which different frictions may reconcile consumption with human capital returns under plausible preference parameters.

[11] The reason is that differences in mean-variance frontiers imply differences in the set of feasible m's, which *may* be attributed to differences in human capital frictions (e.g., borrowing constraints, transaction costs).

[12] Because human capital is illiquid and it is generally impossible for individuals to hold more than one type of human capital asset (except perhaps through marriage, altruism, and other arrangements within the family), differences in rates of return cannot typically be arbitraged out.

[13] See Lawrence Katz and Kevin M. Murphy (1992), for example, for a detailed description of the main features of the wage data and for how top-coding and bracketing are typically dealt with. The same procedures are followed here. The changes in educational attainment questions that occurred in 1992 in the CPS are reconciled with the previous questions using the procedure followed by David A. Jaeger (1997). See Murphy and Finis Welch (1992) and Chinhui Juhn et al. (1993) for analyses of the structure of wages and wage differentials during most of our period of analysis.

TABLE 1—MEAN REAL HUMAN CAPITAL RETURNS AND U.S. EQUITY INDEX RETURN FOR 1964–1996

	Males		Females	
	White	Black	White	Black
No high school				
Experience: 1–5	5.9 (6.2)	−5.1 (8.2)	2.0 (5.7)	−5.5 (10.5)
6–15	5.4 (4.7)	−4.0 (8.3)	1.4 (4.9)	−3.9 (10.0)
>15	5.2 (5.3)	−3.1 (10.6)	3.5 (6.3)	−0.6 (9.9)
High school				
Experience: 1–5	13.6 (9.7)	21.9 (16.5)	18.8 (9.3)	20.3 (14.0)
6–15	8.1 (5.9)	15.8 (11.2)	13.7 (10.2)	22.9 (14.3)
>15	5.2 (7.6)	12.3 (8.7)	7.2 (6.7)	12.2 (10.2)
Some college				
Experience: 1–5	6.0 (6.0)	15.0 (9.9)	11.0 (4.7)	10.2 (14.0)
6–15	7.1 (5.4)	9.6 (8.2)	11.2 (5.1)	8.5 (12.3)
>15	7.3 (4.2)	8.8 (8.1)	10.0 (7.5)	9.0 (11.7)
College				
Experience: 1–5	14.2 (11.3)	18.1 (10.1)	16.8 (8.4)	11.1 (8.2)
6–15	9.0 (7.6)	12.6 (9.3)	14.2 (10.4)	13.6 (9.7)
>15	10.2 (9.1)	14.0 (12.3)	9.2 (8.7)	6.0 (9.9)
More than college				
Experience: 1–5	10.5 (4.7)	12.3 (10.5)	12.1 (6.6)	14.2 (8.9)
6–15	10.0 (5.0)	10.4 (8.6)	10.3 (9.4)	20.6 (11.2)
>15	8.7 (8.1)	7.0 (12.0)	11.0 (8.9)	18.3 (12.8)
U.S. equity index return	7.0 (12.7)			

Note: Standard deviations are in parentheses.

B. *Empirical Evidence*

Table 1 reports the basic descriptive statistics of human capital returns $R^h_{e,t+1}$ for the different demographic groups and the U.S. equity index during 1964–1996.

The average rates of return are broadly consistent with previous estimates in the literature for most groups. It is important to note, however, that when compared to the return on the U.S. equity index, mean human capital returns are relatively high and the standard deviation of returns relatively low for most demographic groups. Thus, human capital Sharpe ratios $|E(R^e)|/\sigma(R^e)$ are often much larger than the Sharpe ratio of the U.S. equity index.

This aspect is important since the information on the *relative* variability of human capital rates of return can help to explain a subtle but long standing problem in the literature. This problem arises from the fact that "the private returns to schooling are not nearly large enough to justify the claims of importance made for schooling," as Mark Bils (2000, pp. 59–60) indicates. This is certainly true for the *level* of returns on schooling in many areas of economics where human capital plays an important role. In an attempt to justify these claims, economists and policy makers often indicate that there may be important external effects from increased schooling and school spending. Empirically, however, human capital externalities are either hard to find or negligible [see, e.g., James J. Heckman and Peter J. Klenow (1997) and Daron Acemoglu and Joshua Angrist (2000)]. A more natural resolution, at least in part, to this problem can be offered by simply looking at the reward to variability ratio of the investment; that is, not just at the level of returns but at the Sharpe ratios. There are large differences between human capital Sharpe ratios and financial Sharpe ratios in many instances. The former ones clearly dominate the latter ones for many demographic groups at different education and experience levels. Note, however, that although broad differences in Sharpe ratios are clearly informative, the covariance structure of returns also plays a key role in determining differences in risk-adjusted returns. We turn next to testing for these differences in investment returns.

As indicated earlier, we consider the GMM-based test of spanning in terms of volatility bounds on the IMRS proposed by De Santis (1993) and the likelihood ratio test proposed by

Huberman and Kandel (1987). In addition to these tests, we also report the increase in the expected return per unit of risk that is obtained when additional returns are included in the original set: $\Delta\sigma(m)$.[14] In our case, we consider the hypothesis of mean-variance spanning when adding just one asset to a benchmark set of returns.[15]

Table 2 shows the p-values of the results of the tests for different human capital returns, for given education and experience groups, across sex and race characteristics. The null hypothesis of spanning is that the frontier associated with the human capital returns of a given demographic group (benchmark returns) coincides with the frontier associated with the returns of that demographic group plus the human capital returns of a different demographic group.

Before discussing specific findings, it is worth noticing the following general patterns. First, the results of the GMM and likelihood ratio (LR) tests are very similar. In virtually all cases considered, these two tests agree on whether or not the null hypothesis of mean-variance spanning should be rejected at conventional significance levels. Second, there is a robust relationship between the indicator of the estimated increase in expected returns per unit of risk $\Delta\sigma(m)$ and the p-value of the tests. As a general pattern, when p-values are greater than 0.40 the indicator ranges from 1 to 3 percent, when p-values are between 0.30 and 0.10 the indicator ranges from 4 to 9 percent. More importantly, when the null hypothesis of coincidence of frontiers is rejected at conventional levels, the indicator ranges from 9 to 14 percent for p-values between 0.10 and 0.05, and from 14 to 29 percent for p-values between 0.05 and 0.00. The following features can be observed in the specific comparisons across groups:

WHITE MALES.—For education levels below college, the hypothesis of mean-variance spanning cannot be rejected at conventional significance levels when considering the human capital returns of any demographic group except white females with some college. Interestingly, the hypothesis is rejected in all the cases of a graduate education and, at the level of college education, for all black females.

BLACK MALES.—The pattern of rejections of the hypothesis of mean-variance spanning is quite different for this group. When considering the human capital returns of white males, the hypothesis is rejected in all cases except at the level of graduate education and up to 15 years of experience. In the case of white females, the hypothesis is *always* rejected at conventional significance levels. With respect to black females, the hypothesis is only rejected at college and more than college education levels with fewer than 15 years of experience.

WHITE FEMALES.—In this case, it is very difficult to reject the hypothesis of mean-variance spanning. In fact, no test indicates the rejection of the hypothesis at the 5-percent level. Only white males at lower education levels appear to be closer to induce a rejection at the usual confidence levels, as well as some males at the level of graduate education.

BLACK FEMALES.—The hypothesis is never rejected when considering the human capital returns of black males. Interestingly, the hypothesis is almost never rejected when considering white individuals with at least a college education, but it is strongly rejected for education levels below college.

We conclude from these findings that there are nontrivial differences across some demographic groups with identical human capital holdings. For instance, net gains for white and black females with respect to other groups tend to arise at high levels of education, whereas for white males they arise at education levels up to college. Net losses arise for black individuals, typically at lower levels of education and, especially, for high school and college dropouts, and relative to their white counterparts.

In Table 3 we report the results of mean-variance spanning tests for human capital and financial returns.

In Panel A, we test the hypothesis of spanning when the returns on the U.S. equity index are added to a benchmark of human capital assets for each of the different demographic groups. The results show that the null hypothesis

[14] This indicator can also be used to compute the *net* gain of asset A over asset B as the increase in expected return per unit of risk obtained when adding asset A to asset B minus the increase in expected return per unit of risk that is obtained when adding asset B to asset A.

[15] Under the null hypothesis of coincidence of boundaries, De Santis' GMM-based test statistic is distributed as a χ^2 with 2 degrees of freedom. The likelihood ratio test proposed by Huberman and Kandel (1987) is distributed as an F distribution with $2N$ and $2(T - K - N)$ degrees of freedom. In our case $K = N = 1$ and $T = 33$.

TABLE 2—MEAN-VARIANCE SPANNING TESTS FOR HUMAN CAPITAL RETURNS ACROSS DEMOGRAPHIC GROUPS

Panel A—Benchmark Human Capital Returns: White Males
Additional Human Capital Returns

	Black Males			White Females			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school									
Experience: 1–5	0.37	0.48	3.17	0.25	0.32	6.55	0.42	0.55	3.26
6–15	0.27	0.42	4.11	0.28	0.23	5.15	0.39	0.46	3.00
>15	0.21	0.28	6.32	0.24	0.19	6.29	0.53	0.44	1.86
High school									
Experience: 1–5	0.14	0.28	8.88	0.12	0.20	8.80	0.36	0.42	3.60
6–15	0.10	0.18	9.00	0.21	0.26	7.77	0.23	0.33	6.61
>15	0.09	0.14	8.73	0.08	0.11	12.80	0.12	0.17	8.50
Some college									
Experience: 1–5	0.36	0.53	3.07	0.01	0.00	21.39	0.24	0.26	5.50
6–15	0.21	0.20	6.55	0.02	0.00	19.98	0.22	0.30	4.52
>15	0.13	0.17	7.90	0.12	0.17	8.30	0.09	0.18	8.88
College									
Experience: 1–5	0.12	0.16	8.66	0.12	0.16	8.01	0.03	0.02	16.40
6–15	0.06	0.12	12.50	0.09	0.12	10.40	0.04	0.05	15.31
>15	0.19	0.22	7.20	0.04	0.02	16.88	0.01	0.00	20.57
More than college									
Experience: 1–5	0.04	0.04	15.91	0.04	0.03	15.90	0.00	0.00	26.03
6–15	0.03	0.02	15.86	0.02	0.01	17.46	0.00	0.00	23.40
>15	0.02	0.00	18.22	0.04	0.01	14.52	0.07	0.05	12.70

Panel B—Benchmark Human Capital Returns: Black Males
Additional Human Capital Returns

	White Males			White Females			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school									
Experience: 1–5	0.01	0.00	25.20	0.03	0.00	18.11	0.11	0.13	9.33
6–15	0.03	0.00	19.31	0.04	0.00	16.32	0.20	0.30	7.80
>15	0.10	0.08	10.60	0.05	0.02	15.24	0.09	0.12	12.64
High school									
Experience: 1–5	0.01	0.02	22.22	0.03	0.01	17.70	0.09	0.12	11.21
6–15	0.04	0.00	17.17	0.04	0.00	15.18	0.15	0.18	8.23
>15	0.06	0.05	14.83	0.07	0.05	12.59	0.10	0.14	10.00
Some college									
Experience: 1–5	0.00	0.04	23.00	0.03	0.00	17.24	0.11	0.14	12.36
6–15	0.03	0.00	15.31	0.06	0.05	14.98	0.18	0.23	10.41
>15	0.07	0.04	12.72	0.02	0.01	17.67	0.06	0.07	14.54
College									
Experience: 1–5	0.01	0.03	20.64	0.03	0.01	16.76	0.05	0.01	14.79
6–15	0.05	0.01	14.32	0.07	0.05	12.49	0.04	0.00	16.86
>15	0.11	0.15	10.55	0.06	0.04	13.85	0.14	0.12	8.90
More than college									
Experience: 1–5	0.11	0.10	9.29	0.06	0.02	13.51	0.00	0.00	28.45
6–15	0.17	0.22	8.39	0.03	0.00	15.79	0.17	0.16	8.60
>15	0.06	0.02	12.47	0.04	0.01	14.90	0.12	0.14	9.66

TABLE 2—*Continued.*

Panel C—Benchmark Human Capital Returns: White Females
Additional Human Capital Returns

	White Males			Black Males			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school									
Experience: 1–5	0.11	0.09	8.70	0.19	0.15	6.66	0.29	0.36	5.42
6–15	0.08	0.09	11.02	0.12	0.15	8.49	0.32	0.28	6.15
>15	0.12	0.07	8.22	0.09	0.11	9.15	0.21	0.23	7.34
High school									
Experience: 1–5	0.07	0.06	13.64	0.13	0.19	9.63	0.30	0.48	7.10
6–15	0.09	0.08	11.29	0.12	0.16	8.90	0.37	0.29	4.66
>15	0.15	0.16	7.51	0.12	0.10	8.27	0.32	0.40	4.83
Some college									
Experience: 1–5	0.11	0.15	8.50	0.23	0.30	4.46	0.39	0.40	5.72
6–15	0.08	0.07	11.77	0.09	0.19	10.61	0.25	0.30	4.94
>15	0.06	0.09	13.12	0.12	0.14	10.07	0.21	0.18	7.60
College									
Experience: 1–5	0.07	0.09	12.91	0.07	0.06	12.85	0.24	0.32	7.65
6–15	0.12	0.17	8.28	0.12	0.10	8.34	0.16	0.36	8.50
>15	0.23	0.20	5.43	0.10	0.10	9.24	0.38	0.50	3.02
More than college									
Experience: 1–5	0.14	0.20	8.28	0.08	0.11	12.59	0.32	0.44	4.33
6–15	0.11	0.26	8.80	0.07	0.12	14.00	0.12	0.26	9.07
>15	0.07	0.12	12.02	0.11	0.15	9.21	0.25	0.21	10.12

Panel D—Benchmark Human Capital Returns: Black Females
Additional Human Capital Returns

	White Males			Black Males			White Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school									
Experience: 1–5	0.00	0.00	29.71	0.24	0.28	5.75	0.01	0.00	26.39
6–15	0.00	0.00	26.15	0.12	0.18	8.92	0.02	0.00	24.50
>15	0.00	0.00	25.67	0.23	0.30	5.20	0.04	0.00	24.61
High school									
Experience: 1–5	0.00	0.00	25.51	0.15	0.11	8.29	0.03	0.00	20.90
6–15	0.02	0.01	18.60	0.09	0.15	9.56	0.05	0.02	18.31
>15	0.02	0.00	17.93	0.07	0.10	12.03	0.12	0.14	10.10
Some college									
Experience: 1–5	0.02	0.03	17.34	0.17	0.22	10.50	0.02	0.01	24.99
6–15	0.03	0.01	16.62	0.10	0.11	14.15	0.04	0.01	19.96
>15	0.06	0.00	13.43	0.23	0.18	5.69	0.02	0.00	28.82
College									
Experience: 1–5	0.12	0.15	8.60	0.11	0.19	9.00	0.03	0.03	16.53
6–15	0.13	0.11	8.39	0.22	0.20	6.33	0.08	0.03	15.76
>15	0.16	0.20	7.82	0.07	0.07	12.12	0.12	0.08	10.88
More than college									
Experience: 1–5	0.12	0.15	8.57	0.34	0.48	3.26	0.02	0.00	20.44
6–15	0.21	0.28	6.11	0.10	0.12	9.28	0.23	0.18	7.97
>15	0.12	0.12	8.39	0.07	0.12	14.79	0.10	0.10	14.85

Note: This table reports the p-values of the GMM and LR tests in the GMM and LR columns, respectively, and the estimated increase per unit of risk under column $\Delta\sigma(m)$.

is rejected at the 5-percent level for *all* individuals who have not completed high school, and all males (but, interestingly enough, not females) with a high school education or with some college education (typically college dropouts) and less than 15 years of experience.

TABLE 3—MEAN-VARIANCE SPANNING TESTS FOR HUMAN CAPITAL AND FINANCIAL RETURNS

Panel A—Benchmark: Human Capital Assets

	White Males			Black Males			White Females			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school												
Experience: 1–5	0.03	0.00	17.55	0.00	0.02	23.58	0.03	0.02	17.55	0.02	0.00	18.41
6–15	0.01	0.00	26.66	0.00	0.00	18.64	0.03	0.01	20.92	0.00	0.00	26.90
>15	0.00	0.01	23.47	0.04	0.03	18.37	0.04	0.04	15.38	0.01	0.03	22.28
High school												
Experience: 1–5	0.04	0.02	16.70	0.04	0.01	14.92	0.17	0.22	8.04	0.57	0.71	1.33
6–15	0.04	0.00	18.89	0.04	0.03	20.18	0.27	0.23	6.56	0.77	0.88	0.42
>15	0.09	0.05	9.98	0.21	0.12	7.90	0.33	0.30	3.62	0.41	0.52	2.82
Some college												
Experience: 1–5	0.00	0.03	23.21	0.01	0.03	20.70	0.11	0.17	8.66	0.37	0.41	3.26
6–15	0.01	0.00	20.09	0.03	0.04	15.61	0.21	0.30	7.02	0.05	0.05	14.66
>15	0.23	0.19	5.18	0.17	0.18	8.52	0.09	0.14	9.11	0.28	0.36	4.07
College												
Experience: 1–5	0.48	0.52	2.34	0.73	0.96	0.51	0.47	0.37	2.30	0.80	0.96	0.03
6–15	0.40	0.50	3.32	0.77	0.92	0.40	0.50	0.60	1.82	0.37	0.32	3.76
>15	0.35	0.41	3.51	0.81	0.88	0.26	0.31	0.26	4.00	0.61	0.79	0.92
More than college												
Experience: 1–5	0.43	0.60	2.21	0.30	0.44	4.08	0.67	0.77	0.82	0.66	0.89	0.08
6–15	0.56	0.70	1.09	0.81	0.80	0.11	0.60	0.70	1.17	0.57	0.77	1.21
>15	0.37	0.33	3.08	0.63	0.93	0.92	0.31	0.40	3.89	0.05	0.02	14.88

Panel B—Benchmark: Financial Assets

	White Males			Black Males			White Females			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school												
Experience: 1–5	0.81	0.97	0.40	0.87	0.98	0.02	0.85	0.98	0.02	0.84	0.93	0.01
6–15	0.60	0.78	1.20	0.84	0.99	0.00	0.75	0.82	0.32	0.81	0.90	0.02
>15	0.63	0.80	1.08	0.83	0.99	0.00	0.74	0.80	0.40	0.55	0.62	1.60
High school												
Experience: 1–5	0.35	0.45	3.56	0.60	0.73	0.91	0.22	0.18	6.59	0.14	0.10	8.31
6–15	0.33	0.40	3.89	0.59	0.60	1.10	0.14	0.11	8.17	0.14	0.12	7.02
>15	0.14	0.19	8.23	0.16	0.15	8.22	0.06	0.05	12.26	0.06	0.04	13.19
Some college												
Experience: 1–5	0.81	0.98	0.01	0.76	0.88	0.42	0.10	0.08	10.27	0.14	0.12	9.08
6–15	0.55	0.79	1.19	0.82	0.93	0.09	0.11	0.10	9.26	0.14	0.16	6.74
>15	0.55	0.86	0.56	0.50	0.46	2.00	0.11	0.12	8.39	0.32	0.28	3.56
College												
Experience: 1–5	0.10	0.14	9.09	0.05	0.04	14.26	0.13	0.16	8.86	0.07	0.06	12.63
6–15	0.06	0.05	13.26	0.06	0.03	13.82	0.14	0.20	7.29	0.09	0.08	10.28
>15	0.05	0.05	14.17	0.06	0.02	14.11	0.09	0.12	10.73	0.10	0.05	9.94
More than college												
Experience: 1–5	0.06	0.05	10.26	0.11	0.14	8.23	0.05	0.04	14.07	0.06	0.05	13.28
6–15	0.05	0.04	16.82	0.07	0.06	12.00	0.02	0.01	17.53	0.16	0.12	8.26
>15	0.04	0.03	15.26	0.20	0.21	7.10	0.02	0.01	17.17	0.31	0.25	4.00

Note: This table reports the p-values of the GMM and LR tests in the GMM and LR columns, respectively, and the estimated increase per unit of risk under column $\Delta\sigma(m)$.

Virtually the *opposite* results are obtained in Panel B. In this panel, we test the hypothesis of mean-variance spanning when the human capital returns of the different demographic groups are added to a benchmark of asset returns on the U.S. equity index. In this case, the hypothesis is typically rejected at the usual confidence levels in both the GMM tests and the likelihood ratio tests for college and more than college education levels but, interestingly, never for education levels below college.[16] Note that, as in Table 2, the GMM and LR tests are very similar, and that the relationship between the indicator $\Delta\sigma(m)$ and the p-values of the tests follows the general pattern described above.

These results are important. They indicate that at the level of aggregation of these demographic groups the "losses" from a "low" investment in education relative to risky financial assets can be substantial. The *net* increase in the Sharpe ratio (computed as indicated in footnote 14) for high school dropouts goes from 15 to 26 percent across the different groups, whereas for males with a high school degree and some college it goes from about 13 to 19 percent. Note also that these losses appear to be reduced with the accumulation of experience. Conversely, the "gains" from investments in education relative to financial assets typically come from college and graduate education levels. The net increase in the Sharpe ratio is about 7 to 14 percent for males with at least a college degree, 14 to 17 percent for white females with more than a college degree, and 7 to 13 percent for black females other than the very experienced ones.

Lastly, the tests were also implemented at the aggregate level for various aggregate measures of human capital returns.[17] The hypothesis of mean-variance spanning cannot be rejected when financial returns are added to the set of human capital returns, but it is strongly rejected when human capital returns are added to financial returns. The maximum Sharpe ratio is about 15 percent greater with both sets of returns than with financial returns alone, and only about 1.5–3 percent greater than with human capital returns alone. Thus, the *net* gains for aggregate human capital assets are about 12 to 13.5 percent in terms of expected returns per unit of risk.

C. *Discussion and Interpretation*

The comparisons in the previous subsection were implemented across demographic (sex, race) groups with identical human capital holdings in terms of education and experience groups, and between human capital and financial returns. For many purposes, however, we may want to examine differences across education and experience levels for given demographic characteristics. Using the evidence presented in these tables, these comparisons can be readily made. For instance, risk-adjusted differences between college and high school returns can be obtained by looking at how a college education compares with financial assets and by then looking at how financial assets compare with a high school education for each demographic group. The net estimates of the corresponding risk-adjusted differences in the rate of return per unit of risk can thus be broadly inferred from the tables. Consistent with the findings of a large literature on the college–high school premium, they conclusively indicate a superiority of greater levels of education over lower levels of education.

The comparisons in the previous section also show that differences in risk-adjusted rates of return per unit of risk between human capital and financial assets can be substantial. For instance, the private gains from a college education for a white male per unit of risk are about 7 to 10 percent greater than from investments in financial assets, whereas the losses for most white high school males are about 15 percent relative to financial assets. These results are consistent with Becker's (1993, p. 207) intuition that "while education *seems* to yield a money gain to the *typical* white male college graduate, it may not to the *typical* white male high-school graduate" (italics added). Interestingly, similar evidence is found for females and for blacks as well.

These findings correspond to the period 1964–1996 and can help explain why education and all other skills were accumulated very rapidly during this period. The results also appear to suggest that investments in college (or more) education will continue growing in the future. As indicated earlier, however, the comparisons cannot identify the causes of these risk-adjusted differences. This would require evaluating whether different parametric models for the IMRS are generating the different human capital and financial returns. In principle, human capital assets are not only risky but illiquid as well—they cannot be sold and are rather poor collateral on loans—so a positive liquidity

[16] The only exception is females with a high school education and more than 15 years of experience. Note also that the p-values of the tests for females with a high school education or some college are substantially lower than the p-values for males in the same group.

[17] These results are available from the author in an Appendix upon request.

premium would be associated with human capital. Despite this liquidity premium, however, individuals at lower levels of education typically experience "losses" relative to liquid assets. Differences in taxation may also explain part of these differences. However, "although the differences might be explained by compensating differences in liquidity and taxation, a more reasonable inference would be that the private money gain from college to the typical graduate is greater than what could have been obtained by investing elsewhere" (Becker, 1993, p. 206). Differences in nonmonetary rewards across genders (perhaps because of the division of labor within the family) could also be a source of differences in monetary returns.

With regard to the interpretation of the results for the "typical" individual discussed above, it is important to note that when examining differences in risk-return trade-offs at *any* level of aggregation, some idiosyncratic risk is left out of the calculations. This is commonly done in financial research in the analysis of the properties of indexes of financial returns. However, unlike financial asset returns which yield the same return to all individuals, human capital returns vary across individuals. Interestingly, Kenneth L. Judd's (2000) theoretical analysis shows how when idiosyncratic risk is endogenous the risk premium for human capital may depend on systematic components of risk, not on idiosyncratic risk. In the analysis we control for sex, race, education, and experience levels.[18] We thus refer to the *typical* individual at this level of aggregation. In the next subsection we also discuss the results of the tests once we account for other sources of heterogeneity, and we find very few differences.

Lastly, for some specific public policy implications, the relevant measure is the social rate of return rather than the private rate of return from education and other forms of human capital. These may be different because of differences between social and private costs and returns, due to human capital externalities from a more educated labor force, because schooling may have a signaling value in addition to raising productivity, or because some other factor of production is supplied inelastically.[19] Using evidence from compulsory schooling laws, Acemoglu and Angrist (2000) find that externalities are very small, typically not significantly different from zero. As a result, the risk-adjusted estimates obtained in this analysis may reflect both private and social total gains and losses from human capital investments. Thus, they can provide reliable estimates for various public policy matters.

D. *Additional Empirical Evidence*

The robustness of the empirical findings has been evaluated by examining a number of extensions including the role of tuition costs and the effects of ability and selectivity biases, and by considering other approximations to human capital returns that account for other sources of risk and heterogeneity, including the typical Becker-Mincer approach and the measures suggested by Buchinsky and Leslie (1997) and Campbell (1996). We found very few differences with respect to the previous estimates.[20] The results are available in an Appendix upon request.

[18] Interestingly, when the comparisons in Table 2 and 3 are implemented controlling for occupation and industry in the computation of $R^h_{e,t+1}$, the results are virtually identical to those reported in these tables.

[19] See the discussion in Becker (1993).

[20] Rates of return were estimated from the classical Becker-Mincer log-wage regressions using a set of regressors that includes education, experience, sex, race, nine geographic dummies, metropolitan area, individual and family nonearned income, and marital status. These returns tend to have lower means and lower variances than $R^h_{e,t+1}$, but highly similar Sharpe ratios. The results of the tests of differences in risk-adjusted returns are very similar. Buchinsky and Leslie (1997) develop a dynamic model with endogenous labor supply that accounts for evolving perceptions about future wages. The human capital measures in their model are obtained using a quantile regression approach. Mean returns are similar to $R^h_{e,t+1}$, but they tend to have lower variability, especially for greater education levels. As a result, human capital Sharpe ratios are slightly greater than those corresponding to $R^h_{e,t+1}$. However, the *p*-values of both the GMM tests and the likelihood ratio tests are similar. Only minor differences were found for college dropouts when comparing human capital and financial returns. The measure suggested in Campbell (1996) also induces slightly greater Sharpe ratios than those induced by $R^h_{e,t+1}$. When comparing human capital returns across demographic groups, the *p*-values of the GMM and likelihood ratio tests are essentially identical to those in Table 2. When comparing human capital and financial returns, however, it is slightly easier to reject (accept) the hypothesis that financial (human capital) returns span the same mean-variance space than financial plus human capital returns for education levels above high school.

We have also considered an aspect that is concerned with the measures of financial returns. It might be argued that an appropriate comparison between human capital and financial returns should involve the year to year changes in corporate dividends alone, that is without considering capital gains. If all financial capital gains could be explained by changing expectations of future dividends, then the two measures would be equivalent. But this need not be the case. We thus consider the procedure in Casey B. Mulligan (2002) to measure physical capital returns from the national accounts which, as with the labor market data, have only the "dividend" portion of the return [see Mulligan (2002) for details of the computation of these returns]. This idea has also been followed by a number of authors, including Zvi Griliches and Dale W. Jorgenson (1966), Martin S. Feldstein and Lawrence Summers (1979), Feldstein et al. (1983), and others. The results of the tests of mean-variance spanning between human and physical capital returns are shown in Table 4.

Two interesting features are worth noticing. First, the p-values of the tests are very similar to those in Table 3. This result is consistent with the idea (but does not imply) that financial capital gains are largely associated with changing expectations of future dividends. Second, when the null hypothesis of coincidence of boundaries is rejected, the indicator $\Delta\sigma(m)$ of the gains per unit of risk is consistently lower (on average about 20 percent lower) than the indicator obtained for financial returns, although still sizable.

We conclude from these findings that the results obtained above are largely consistent with those obtained using other approximations of human capital returns and with those obtained for physical capital returns.

IV. Concluding Remarks

The analysis of capital returns, both human and financial, provides a backdrop for, and the subject matter of, several important areas of economics (human capital, labor economics, finance). They are also important in many public policy areas, and in models of economic growth and development, macroeconomics, and business cycles where microestimates of human capital returns play a fundamental role in calibrations and empirical analyses. The principal novelty of this work is as a contribution to economics centers on its attempt to provide an analysis of the risk-return properties of human capital returns and a comparison with other investments overcoming the difficulties that have persisted in the literature for the last few decades.

The empirical analysis has yielded a number of results. In particular, the variation in the stochastic properties of different human capital returns is substantial, especially when comparing human capital and liquid assets. These differences indicate how much is gained or lost by individuals and society from investments in human capital assets relative to financial investments. The analysis cannot identify the sources of these risk-adjusted differences, but it does suggest that some "difficulties," "frictions," or costs of trading claims on the present discounted value of future wages may be present for some individuals, especially at low education levels and for some minorities. The empirical analysis can also explain the superiority of human capital, at least at college levels, over liquid investments. While the level of private returns to schooling in the literature is not sufficient to justify the claims of importance made for education in many areas of economics, the analysis shows how it is possible to justify the superiority of investments in schooling by simply accounting for the riskiness of the investments.

The analysis can also be useful in other areas. For instance, to the extent that marriage and families serve to hedge some risks and to diversify human capital investments through altruism or implicit contracts, the analysis may be useful to the understanding of marriage and divorce markets, the structure of the family, and investments in the human capital of children. It may also shed light on the behavior of individuals regarding their allocations among risky financial assets (bonds and stocks) and nontraded assets such as human capital.[21] The empirical

[21] See, for instance, Niko Canner et al. (1997) and Luis Viceira (2001). Steven Davis and Paul Willen (2000) evaluate the portfolio choice and welfare implications of hedging labor income risks with financial assets. The results in our analysis indicate that the less educated individuals would be the ones that could benefit the most from access to financial markets perhaps, for instance, through 401k and similar plans.

TABLE 4—MEAN-VARIANCE SPANNING TESTS FOR HUMAN AND PHYSICAL CAPITAL RETURNS

Panel A—Benchmark: Human Capital Assets

	White Males			Black Males			White Females			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school												
Experience: 1–5	0.02	0.02	14.81	0.00	0.00	18.90	0.01	0.01	15.22	0.03	0.00	15.06
6–15	0.00	0.01	22.70	0.00	0.00	16.02	0.00	0.01	15.33	0.02	0.00	21.88
>15	0.03	0.02	19.69	0.02	0.03	15.17	0.03	0.04	11.77	0.03	0.00	17.93
High school												
Experience: 1–5	0.04	0.00	14.02	0.00	0.02	13.18	0.21	0.32	6.33	0.71	0.75	0.83
6–15	0.03	0.01	15.21	0.04	0.04	15.88	0.25	0.30	5.06	0.63	0.56	1.32
>15	0.07	0.03	8.13	0.26	0.10	7.07	0.39	0.40	3.12	0.52	0.64	0.91
Some college												
Experience: 1–5	0.03	0.03	19.07	0.02	0.01	18.11	0.10	0.29	6.16	0.21	0.46	2.66
6–15	0.02	0.05	17.30	0.02	0.05	12.88	0.17	0.25	5.17	0.07	0.08	11.50
>15	0.27	0.22	4.61	0.22	0.17	7.23	0.07	0.17	6.07	0.31	0.52	3.21
College												
Experience: 1–5	0.38	0.42	1.89	0.60	0.76	0.67	0.58	0.47	1.57	0.84	0.72	0.03
6–15	0.51	0.39	2.84	0.57	0.90	0.30	0.41	0.54	0.92	0.69	0.48	2.90
>15	0.37	0.51	3.31	0.72	0.92	0.11	0.60	0.38	2.33	0.82	0.91	0.08
More than college												
Experience: 1–5	0.44	0.62	2.01	0.21	0.34	3.71	0.81	0.70	0.09	0.71	0.74	0.08
6–15	0.50	0.57	0.88	0.83	0.82	0.20	0.72	0.60	0.60	0.82	0.64	0.55
>15	0.41	0.40	2.53	0.89	0.77	0.63	0.28	0.41	1.28	0.04	0.01	12.12

Panel B—Benchmark: Physical Capital Assets

	White Males			Black Males			White Females			Black Females		
	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$	GMM	LR	$\Delta\sigma(m)$
No high school												
Experience: 1–5	0.65	0.73	0.63	0.63	0.80	0.00	0.85	0.88	0.02	0.90	0.99	0.00
6–15	0.47	0.82	0.92	0.90	0.87	0.00	0.75	0.95	0.00	0.89	0.70	0.03
>15	0.58	0.71	0.81	0.98	0.96	0.00	0.74	0.99	0.09	0.77	0.77	0.87
High school												
Experience: 1–5	0.46	0.55	2.34	0.78	0.88	0.28	0.22	0.18	5.40	0.16	0.10	6.80
6–15	0.43	0.74	1.20	0.84	0.75	0.83	0.14	0.21	6.53	0.08	0.17	5.53
>15	0.21	0.21	6.50	0.22	0.11	6.82	0.06	0.10	11.22	0.08	0.03	9.82
Some college												
Experience: 1–5	0.72	0.83	0.09	0.92	0.64	0.41	0.10	0.10	8.23	0.21	0.20	6.60
6–15	0.64	0.92	0.12	0.63	0.76	0.50	0.11	0.15	6.66	0.16	0.17	5.40
>15	0.41	0.64	0.40	0.21	0.85	0.90	0.11	0.08	6.82	0.44	0.41	3.22
College												
Experience: 1–5	0.08	0.12	7.50	0.04	0.09	12.06	0.13	0.11	7.44	0.03	0.15	9.90
6–15	0.08	0.05	11.02	0.09	0.06	11.12	0.14	0.19	5.94	0.11	0.16	8.02
>15	0.03	0.06	11.60	0.08	0.07	11.02	0.09	0.08	8.66	0.02	0.09	9.03
More than college												
Experience: 1–5	0.05	0.11	9.12	0.12	0.08	7.82	0.05	0.00	11.40	0.07	0.04	10.44
6–15	0.03	0.07	13.66	0.03	0.03	9.50	0.02	0.01	14.04	0.10	0.10	7.06
>15	0.02	0.06	12.08	0.08	0.05	5.92	0.02	0.00	13.55	0.62	0.40	2.12

Note: This table reports the p-values of the GMM and LR tests in the GMM and LR columns, respectively, and the estimated increase per unit of risk under column $\Delta\sigma(m)$.

results may also be relevant to determine the optimal social rate of discount to use in evaluating benefit and cost streams from public investment (e.g., public education), and for the analysis of intertemporal substitution in consumption [Robert E. Hall (1988); Mulligan (2002)].

Lastly, to the extent that the restrictions imposed on the IMRS are different for different human capital assets, and given that *all* individuals hold human capital assets, the analysis has implications for the properties of valid IMRS for models of dynamic economies and for some compelling questions in these fields: What are the fundamental sources of individual and aggregate risk? How does risk affect the allocation of the different classes of capital? After all, "ultimately, a satisfying model of risk and return must explain the magnitudes of the rewards that investors receive for bearing *different kinds of risk*" (Campbell, 1996, p. 342). An open, important question for future research is that of finding the classes of models, preferences, and market structures that may be consistent with human capital returns. The different restrictions imposed on the IMRS by different human capital assets suggest that they may greatly vary across education levels and individuals.

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