The Robustness of the Conditional CAPM with Human Capital

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ABSTRACT
An empirical evaluation is provided of the robustness of the conditional capital asset pricing model (CAPM) with human capital to explain the cross-sectional variability of security returns. This model has been evaluated in the literature using the growth rate in per capita labor income. This article looks at richer measures of human capital returns. It develops measures that incorporate the costs and benefits of educational investment, skill premiums, worker experience, and other relevant features of human capital markets. It also considers variables that help to forecast future human capital returns. We find that some of these richer measures help improve substantially the performance of the model.

KEYWORDS: CAPM, human capital, securiy returns, labor market.

The important role that human capital plays in individual and aggregate wealth suggests that a potentially fruitful way to test the operational validity of the capital asset pricing model (CAPM) may be to incorporate human capital assets as part of the market or wealth portfolio. Jagannathan and Wang (1996; henceforth JW) pursue this avenue. They develop a dynamic, conditional CAPM that includes human capital where betas are allowed to vary over time. They approximate the return to aggregate human capital wealth by the growth rate in per capita labor income and find that the model can explain about 55% of the variability of the average returns of the U.S. portfolios that they examine. This important result is considered to be of great relevance for financial economists and practitioners.[1]

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[1] Fama and Schwert (1977), Liberman (1977), Mayers (1972, 1973), and Williams (1978) explored this avenue for evaluating the *static* CAPM. Using the same approximation to the return to aggregate human capital wealth, they found that human capital did not exert any meaningful influence on either the pricing of risky financial assets or portfolio composition.

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As JW acknowledge, however, "the use of the growth rate in labor income is rather *ad hoc*" (p. 14). In fact, this measure is limited in several respects. For instance, it does not account for the capital gains of the stock of human capital, it assumes that labor supply is exogenous, it ignores skill premia and the role of worker experience, and it does not net out the effect of physical capital on labor income and human capital returns.

This article develops more sophisticated measures of human capital returns that account for these and other shortcomings. These measures, and others recently developed in the literature, are then used to provide an empirical characterization of the robustness of the conditional CAPM with human capital. The motivation is that it is important to know which types of labor market risks may be priced in financial assets. We find that the performance of the model may improve substantially with respect to the implementation of the model in which human capital returns are approximated by the growth rate in per capita labor income. In particular, the analysis identifies labor market risks associated with capital gains and skill premia in human capital markets and with variables that help forecast future human capital returns as important sources of cross-sectional variation in financial asset prices. These results are relevant for empirical analyses of asset pricing models, risk management, and for applications in the finance, labor, and macroeconomics literature.

1 MEASURES OF AGGREGATE HUMAN CAPITAL RETURNS

Over the past decade there has been a resurgence of effort in the very difficult task of uncovering the causal effect of investments in human capital in the labor market. Card (2001) offers a survey of the recent literature on estimating the economic returns to education and the econometric problems that persist. Given that a number of related approaches are available in the literature, we will consider different measures of aggregate human capital returns in this article. In this section we first describe the approximations developed in the finance literature that allow for changes in expected future labor income and expected future financial returns to have an effect on the measurement of the returns to human capital. We then develop two measures of human capital returns that are closely related to the classical model of endogenous schooling in the labor economics literature. Lastly, we briefly describe the typical method to compute the internal return to investments in education.

1.1 Revisions in Expected Future Labor Income and Future Financial Returns

Campbell (1996) assumes that labor income is exogenous and considers the market return as a linear combination of the financial return R^{vw}_{t+1} and the human capital return R^{hk}_{t+1}. He shows that if the conditional expected return on financial wealth and human capital wealth are equal, then a log-linear approximation implies that

$$r_{t+1}^{hk} = E_t r_{t+1}^{hk} + (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \triangle \log w_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}^{vw},$$

where w denotes labor income and the lowercase variables are the logarithm of the uppercase counterparts. This approximation implies that increases in expected future labor income cause a positive return on human capital and that increases in expected future financial asset returns cause a negative return because the labor income stream is discounted at a higher rate.

Other authors have considered special cases of this measure. Shiller (1993), for instance, discounts labor income at a constant rate: $(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}^{vw} = 0$. JW (1996), in addition to discounting labor income at a constant rate, assume that labor income growth is unforecastable, $(E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \triangle \log w_{t+1+j} = 0$ for $j > 0$, and only consider the rate of growth in per capita labor income. We will refer to these three measures as the Campbell measure, the Shiller measure, and the Jagannathan–Wang measure, respectively.

The econometric methodology used to compute these measures follows Campbell (1996) and adapts the vector autoregressive (VAR) approach in Campbell (1991) as follows. We construct a five-element state vector $\mathbf{z}_t$ with the following variables: a value-weighted real stock index return (RVW), the real labor income growth rate (LBR), the dividend yield on the value-weighted real stock index (DIV), the "relative bill rate" (RTB) (defined as the difference between the one-month Treasury bill rate and its one-year backward moving average), and the yield spread between long- and short-term government bonds (TRM). We then assume that this vector $\mathbf{z}_t$ follows a first-order VAR: $\mathbf{z}_{t+1} = \mathbf{A} \cdot \mathbf{z}_t + \boldsymbol{\epsilon}_{t+1}$ with $\mathbf{z}_t \perp \boldsymbol{\epsilon}_{t+1}$. This VAR generates simple multiperiod forecasts of future returns: $E_t \mathbf{z}_{t+1+j} = \mathbf{A}^{j+1} \mathbf{z}_t$.

1.2 Models of Endogenous Schooling

In the typical human capital investment model, the price p_t of an additional unit of human capital can be written as the discounted sum of future benefits $\{d_{t+j}\}$ that this unit will provide for the rest of life. Using a risk-adjusted discount factor R, it may be written as $p_t = \sum_{j=1}^{\infty} d_{t+j}/R^j$. Alternatively the price may be written using a generally defined stochastic discount factor.[2] The three measures discussed above capture a number of relevant features of the returns to human capital. However, they abstract from variations in work effort, skill premiums, and other aspects that might be important determinants of the rate of return to schooling in a fully specified model with endogenous labor supply. In this subsection we develop two aggregate measures that are consistent with such a model.

[2] If the stochastic discount factor is denoted by $m_{t,t+j}$, then using the transversality condition that $\lim_{j\to\infty} E_t[m_{t,t+j} p_{t,t+j}] = 0$, we can write $p_t = \sum_{j=0}^{\infty} m_{t,t+j} d_{t+j}$ [see Cochrane (2001)]. The transversality condition is rather natural in human capital markets since human capital assets cannot be sold.

1.2.1 A value-weighted index of individual returns In the classical dynamic optimization model with endogenous labor supply, individuals decide in each period their current consumption and whether to attend school or gain a year of work experience [see Becker (1993), Buchinsky and Leslie (1997), and Card (2001)]. Thus *individual* human capital returns may be computed as follows. Consider an individual i at time t with $e-1$ years of education who is to decide whether to invest in education or work and acquire one more year of experience. If he decides to go to school for one period now rather than next period he will earn nothing at t and will expect to earn $w^i_{e,t+1}$ dollars, in real terms, at $t+1$. If instead he decides to go to school next period and work this period, he will earn $w^i_{e-1,t}$ real dollars now and nothing next period. As a result, the marginal human capital return can be computed as

$$r^i_{e,t+1} = \frac{w^i_{e,t+1}}{w^i_{e-1,t}}.$$

A relevant characteristic of this measure is that it captures the per period *capital gains* obtained from owning a stock of $e-1$ units of human capital at t, as well as the *skill premium* associated with having greater skills at the margin. Note that it can be decomposed as

$$r^i_{e,t+1} = \frac{w^i_{e,t}}{w^i_{e-1,t}} \cdot \frac{w^i_{e,t+1}}{w^i_{e,t}} = r^t_{e-1,e} \cdot r^e_{t,t+1}.$$

The second fraction, $r^e_{t,t+1}$, captures the capital gains, while the first one, $r^t_{e-1,e}$, captures the skill premium that arises from having one more unit of human capital at a given time.[3] The fact that this measure accounts for capital gains and skill premia means that it is fundamentally different from the growth rate in labor income and the Shiller and Campbell measures.[4]

These individual marginal returns can then be aggregated in a value-weighted fashion across the demographic characteristics of interest c,

[3] This measure not only applies to young individuals investing early in their lives in education or other forms of human capital, it captures the *premium* necessary to "move" *any* given individual, regardless of his age, from t to $t+1$ from his current life-cycle wage profile (that of someone with e units of human capital) to that of someone with 1 more unit of human capital.

[4] It is straightforward to express $r^i_{e,t+1}$ as the present discounted value of all the additional dividends that that unit of human capital will provide for the rest of life. Intuitively, note that the numerator and the denominator of $r^i_{e,t+1}$ are different in one unit of human capital. However, the numerator of the growth rate in per capita labor income will be associated with 0.15–0.2 more units of human capital, rather than with 1 more unit, given that over the last two decades the average number of years of education in the population has increased by three to four years. Moreover, contrary to Campbell (1996), this approximation does not assume that the conditional expected return on financial wealth and human capital wealth are equal. The evidence presented in Palacios-Huerta (2003) rejects this assumption. However, relative to the Campbell and Shiller measures, $r^i_{e,t+1}$ does not include the effects of revisions in future labor income and future discount rates.

where the weights are given by the average wage $w^c_{e,t+1}$ of individuals in demographic group c with education e relative to the value of all average wages across education and demographic characteristics:

$$\mathcal{R}^I_{t+1} = \sum_e \sum_c s^e_c \frac{w^c_{e,t+1}}{w^c_{e-1,t}} \quad \text{with } s^e_c = \frac{w^c_{e,t+1}}{\sum_e \sum_c w^c_{e,t+1}}.$$

The risk-return properties of these returns are studied in detail at the level of sex, race, education, and experience characteristics in Palacios-Huerta (2003). These are also the characteristics that we will consider here to compute $\mathcal{R}^I_{t+1}$.

1.2.2 An average aggregate return It is also of interest to measure the return associated with the investments at time t that are necessary to obtain the actual *distribution* of educational attainments in the population at $t+1$. This measure can be computed intuitively as follows. Consider, just for descriptive convenience, the following question: "How can a society "create" one college graduate (16 years of schooling) at time $t+1$ from a high school graduate (12 years of schooling) at time t?" This is generally an impossible task for a single individual to accomplish in one year. Yet it is not impossible from an aggregate perspective. Let us assume that a high school graduate needs four years to complete a four-year college education, and that we have four people with 12, 13, 14, and 15 years of education at time t, respectively. If each of these four people invests in education for one year, at time $t+1$ they will have 13, 14, 15, and 16 years of education, respectively. This means that at time $t+1$ there will be only one change in the aggregate distribution of educational attainments in the population with respect to the one at time t: it will still have one individual with 13, one with 14, and one with 15 years of education, but instead of having one individual with 12 years of education it will have one with 16 years of education.

This thought exercise shows that the college-high school premium can be approximated as $\sum_{e=13}^{16} w_{e,t+1} / \sum_{e=12}^{15} w_{e,t}$. It is then straightforward to see that the investment necessary at time t to produce the observed distribution of individuals at time $t+1$ with 13, 14, 15, and 16 years of education, $N_{i,t+1}$, $i = \{13, \ldots, 16\}$, using high school graduates as inputs is $\sum_{e=13}^{16} [\sum_{i=e}^{16} N_{i,t+1}] w_{e-1,t}$. This investment will yield $\sum_{e=13}^{16} [\sum_{i=e}^{16} N_{i,t+1}] w_{e,t+1}$ at $t+1$, and the return from the investment can be easily measured. Similarly, if instead of the premium over high school we consider that the full return to human capital is the premium relative to individuals with *no* human capital,[5] then the aggregate human capital return can be approximated as

$$\mathcal{R}^S_{t+1} = \frac{\sum_{e=1}^{E} [\sum_{i=e}^{E} N_{i,t+1}] w_{e,t+1}}{\sum_{e=1}^{E} [\sum_{i=e}^{E} N_{i,t+1}] w_{e-1,t}},$$

[5] Mulligan and Sala-i-Martin (1997) suggest measuring human capital returns as the premium relative to having *no* human capital. The reason is that this nets out the effects of physical and other forms of capital on human capital returns.

where $E = \max\{e\}$. This ratio is exactly the return associated with the actual aggregate distribution of education attainments relative to the situation where no individual has any human capital.

An advantage of this measure is that it nets out the effects of physical capital. A possible shortcoming is that it is not a marginal individual return of human capital that is associated with the equilibrium conditions of a dynamic optimization model at the individual level. Yet the implicit return in the changes that take place in the distribution of educational attainments may represent a relevant labor market risk that drives security returns.

1.3 The Becker–Mincer Approach

The typical method used to calculate the rate of return on human capital in the labor economics literature was first presented by Mincer (1958) and later expanded by Becker (1964) and other authors. It is based on the maximization of the present discounted value of wealth associated with some choice in the amount of schooling. As a result, after adjusting the income data for age and experience, a linear regression of the logarithm of income (wages) on years of schooling yields an estimate of the internal rate of return to education as the regression coefficient on years of schooling. Much of the research in the human capital area has been organized around this method. Following this method we will estimate Becker–Mincer measures of human capital returns by regressing the logarithm of monthly wages on a set of regressors that include education, experience, dummies for sex, race, nine geographic dummies, a standard metropolitan statistical area (SMSA) dummy, individual and family nonearned income, marital status, and a dummy variable for whether the individual has any children.[6]

It is important to note the differences with respect to the previous measures. The Becker–Mincer measures are an average internal rate of return rather than an individual marginal return to education. As Card (2001: 1157) indicates, "the Becker–Mincer framework immediately focuses attention on the rather special conditions that are required in order for the labor market to be characterized by a unique return to education. ... In general, the marginal return to education to the last unit of education may be either above or below the average return in the population as a whole." A value-weighted index of marginal individual returns such as $\mathcal{R}^I_{t+1}$ may well be substantially different than the average internal rate of return in the population. A second difference is that capital gains are not measured in the Becker–Mincer approach. The regression coefficient on years of schooling in the semilogarithmic form adopted in the literature captures an average internal skill premium but does not capture the change in value of the existing stock of human capital. These capital gains, which are on average about 2% in the United States, may also represent a relevant labor market risk.

[6] See Card (2001) for a thorough survey and evidence on these basic measures of human capital returns in different datasets.

2 EMPIRICAL EVIDENCE

2.1 Data

2.1.1 Human capital data The wage data come from the Current Population Surveys (CPS) for the period 1964–1990. We use the CPS data in the annual March survey for 1964–1978 and in the monthly Earners Study for 1979–1990, which provide information on earnings and weeks worked on a monthly and yearly basis, respectively, for approximately 1.4 million workers. The data are initially divided into 4320 distinct groups, distinguished by the following demographic characteristics: sex, race (white, black, others), years of education (1–18 or more), and potential years of experience (from 0 to 40), defined as min{*age* − *years of schooling* − 7, *age* − 17}, where age is the age at the survey date. Observations are then grouped according to their sex, race, five educational attainment groups (no high school, high school, some college, college, more than college), and three experience groups (1–5, 6–15, and more than 15 years of experience). The average monthly wage of full-time workers is computed within each gender–race–education–experience cell as total monthly earnings deflated by the personal consumption expenditure deflator from the National Income and Product Accounts. These are the wages used in the construction of returns $\mathcal{R}^I_{t+1}$ and $\mathcal{R}^S_{t+1}$.[7] For the counts $N_{i,t+1}$ in the construction of $\mathcal{R}^S_{t+1}$ we use the weights supplied in the CPS data files to expand the counts to nationally representative levels. Lastly, the growth rate in per capita labor income (LBR) used in the Campbell, Shiller, and JW measures is constructed as the percentage change in the two-period moving average per capita labor income from the National Income and Product Accounts. All nominal variables are deflated by the personal consumption expenditure deflator.

2.1.2 Financial data The data on the value-weighted index return of stocks RVW, the index DIV, and the RTB come from the Center for Research in Security Prices (CRSP). The data for the TRM are obtained from the *Federal Reserve Bulletin*. In order to produce a comparison with JW's findings that are as close as possible, we use the same portfolios, data, and FORTRAN programs.[8] They create 100 portfolios of New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) stocks. Starting in July 1963, firms are sorted into size deciles. For each decile, betas for each firm are estimated. Then firms are sorted within each size decile into beta deciles based on their betas and the return on each of these 100 beta-size portfolios is computed for the next 12 calendar months. This is done for each calendar year

[7] The monthly average wage can be readily computed for the period 1979–1990 from the CPS Earners Study. For the period 1964–1978, it is computed from the CPS March survey as total annual earnings divided by total months worked. We follow Katz and Murphy (1992) when dealing with top-coding and bracketing in the data.

[8] These were available at ftp.socsci.umn.edu.

Table 1 Summary statistics for the real human capital return series.

	Campbell	Shiller	JW	R^I	R^S	Becker–Mincer
Mean	1.245	0.832	0.574	1.122	0.320	0.501
Std. deviation	0.724	0.331	0.289	0.479	0.021	0.123
Correlations						
Campbell	1.000	0.522	0.114	0.278	0.034	0.082
Shiller		1.000	0.266	0.170	−0.016	0.040
JW			1.000	−0.132	0.068	−0.038
R^I				1.000	−0.100	0.076
R^S					1.000	0.414
Becker–Mincer						1.000

This table gives the monthly means, standard deviations, and correlations of real human capital returns over the period 1964–1990. The Jagannathan–Wang (JW) return is the percentage change in the two-period moving average per capita labor income from the National Income and Product Accounts. The Campbell returns are computed using the VAR approach described in the text. The Shiller returns are constructed in a similar way except that labor income is discounted at a constant rate. The measures R^I and R^S are computed using the monthly average wages taken from the Current Population Survey (CPS) by gender, race, education, and experience. The counts $N_{i,t+1}$ for computing R^S are taken from the weights supplied by the CPS. The Becker–Mincer return is computed by regressing the logarithm of monthly wages from the CPS on education, experience, sex, race, geographical dummies, standard metropolitan statistical area, individual and family nonearned income, marital status, and a dummy variable for whether the household has any children. All returns are deflated by the personal consumption expenditure deflator from the National Income and Product Accounts.

for the period July 1963–December 1990. The result is 330 observations for each of the 100 portfolios.[9]

The summary statistics that describe the basic characteristics of the different measures of returns to human capital are collected in Table 1.

2.2 Empirical Results

We use the following notation. The return on portfolio i ($i = 1, 2, \ldots, 100$) in month t is denoted by R_{it}, R_t^{vw} denotes the value-weighted index of stocks, and R_t^{prem} is the yield spread between low-grade and high-grade corporate bonds. The β_i^{vw} is the slope coefficient in the ordinary least squares (OLS) regression of R_{it} on a constant and R_t^{vw}, and other betas are estimated in a similar way. R_t^{hk} is the aggregate return on human capital assets. Portfolio size is denoted by $\log(ME_i)$ and is computed as the equally weighted average of the logarithm of the market value of the stocks in portfolio i.

We will present empirical evidence from different regression models and models for the moments that is readily comparable with JW (1996). The regression models are estimated using the Fama–MacBeth procedure. The models for the moments are estimated using the generalized method of moments (GMM) with

[9] See JW (pp. 19–21) for a detailed description of the procedure and for the basic characteristics of these 100 portfolios during the period of analysis.

Table 2 Evaluation of the static and conditional CAPM specifications without human capital.

Static CAPM without human capital					
Coefficient	c_0	c_{vw}	c_{prem}	c_{size}	R^2
Estimate	1.24	−0.10			1.35
t-value (p-value)	5.17 (0.00)	−0.28 (78.00)			
Estimate	2.08	−0.32		−0.11	57.56
t-value (p-value)	5.79 (0.00)	−0.94 (34.54)		−2.30 (2.14)	
Coefficient	δ_0	δ_{vw}	δ_{prem}		HJ-dist (p-value)
Estimate	0.97	1.55			0.6538 (0.22)
t-value (p-value)	89.01 (0.00)	1.09 (27.59)			
Conditional CAPM without human capital					
Coefficient	c_0	c_{vw}	c_{prem}	c_{size}	R^2
Estimate	0.81	−0.31	0.36		29.32
t-value (p-value)	2.72 (0.66)	−0.87 (38.45)	3.28 (0.10)		
Estimate	1.77	−0.38	0.16	−0.10	61.66
t-value (p-value)	4.75 (0.00)	−1.10 (27.57)	2.50 (1.26)	−1.93 (5.35)	
Coefficient	δ_0	δ_{vw}	δ_{prem}		HJ-dist (p-value)
Estimate	1.48	2.05	−45.94		0.6425 (0.98)
t-value (p-value)	6.71 (0.00)	1.47 (14.14)	−2.36 (1.83)		

This table gives the estimates for the cross-sectional regression model and the moments model:

$$E[R_{it}] = c_0 + c_{size}\log(ME_i) + c_{vw}\beta_i^{vw} + c_{prem}\beta_i^{prem}$$
$$E[R_{it}(\delta_0 + \delta_{vw}R_t^{vw} + \delta_{prem}R_t^{prem})] = 1.$$

The return on portfolio i ($i = 1, 2, \ldots, 100$) in month t is denoted by R_{it}, R_t^{vw} is the value-weighted index of stocks, and R_{t-1}^{prem} is the yield spread between low- and high-grade corporate bonds. The β_i^{vw} is the slope coefficient in the OLS regression of R_{it} on a constant and R_t^{vw}. The other betas are estimated in a similar way. The portfolio size, $\log(ME_i)$, is calculated as the equally weighted average of the logarithm of the market value (in million dollars) of the stocks in portfolio i. The regression models are estimated by using the Fama–MacBeth procedure. The models for the moments are estimated by using the GMM with the Hansen–Jagannathan weighting matrix. The minimized value of the GMM criterion function is the first item under "HJ-dist," with the associated p-value immediately below it. Source: Estimates are reproduced from Jagannathan and Wang (1996, Table II).

the Hansen and Jagannathan (1991) weighting matrix. The minimized value of the GMM criterion function will be denoted by "HJ-dist."[10]

Table 2 reproduces some of JW's findings for both the static and conditional specifications of the CAPM without human capital. When portfolio size is not taken into account, the static CAPM is able to explain only 1.35% of the

[10] The reader is referred to JW (1996) for a detailed description of the econometrics methodology. We will report the t-values and p-values for the coefficients of the Fama–MacBeth regressions and the models for the moments. The corrected t-values and corrected p-values that account for sample size were also computed for each test and each coefficient. They are not qualitatively different from those presented in the tables, and are available upon request.

cross-sectional variation in the 100 beta-size portfolios. However, when portfolio size is part of the model it is able to explain up to 57.56%. In the conditional CAPM, these percentages improve up to 29.32% and 61.66%, respectively. Portfolio size has a strong effect in the static CAPM, but it is not significant in the conditional CAPM. Of interest is that the pricing error in both of these models is statistically different from zero. As will be shown next, when human capital is included in the conditional CAPM model, the pricing error is zero for most of the human capital measures that we consider.

The main findings of the article are collected in Tables 3 and 4. In Table 3, the performance of the conditional CAPM is evaluated using the measures of aggregate human capital returns discussed previously for the same cross-sectional regression and moments models as in Table 2.

The first three measures we examine are very related to each other. As discussed earlier, the Shiller measure considers, in addition to the growth rate in per capita labor income, changes in expected future financial returns. The Campbell measure, relative to the Shiller measure, also accounts for revisions in expected future labor income. JW found strong support for the conditional CAPM using the growth rate in per capita labor income. The findings for the regression models show that the support for the model is *stronger* with the Shiller measure, and even stronger with the Campbell measure. When the effect of portfolio size is not considered, the R^2 of the models increases from 55.21% with the growth rate in per capita labor income to 58.11% and 60.02% with Shiller and Campbell measures, respectively. When portfolio size is considered, the R^2 increases from 64.73% to 65.06% and 66.92%, respectively. These measures therefore induce a moderate but valuable improvement in the empirical ability of the conditional CAPM. The hypothesis that the pricing errors are zero cannot be rejected in either of the three cases.[11]

The evidence from the moments model confirms these findings. The HJ-dist statistic decreases for the Shiller measure and even more for the Campbell measure. The p-values indicate that the hypothesis that the pricing errors in these models are zero cannot be rejected. Also, in the cross-sectional regressions both c_{hk} and c_{prem} are significant in all three cases, and they are most significant when using the Campbell measure. Consistent with this result, the p-values of the coefficients δ_{hk} and δ_{prem} are lowest for the Campbell measure. Of interest is that the coefficients for the value-weighted index of stocks and for portfolio size are never significant in any of these three cases. When these results are compared with those of the conditional CAPM without human capital in Table 2, it appears that most of the improvement in the specification is captured by the growth rate in per capita labor income. Yet accounting for changes in expected future financial returns and

[11] R^2's are a measure of goodness-of-fit and not a direct statistical criterion to compare models. For this reason we implemented the likelihood ratio tests for differences in R^2's in nonnested models developed in Vuong (1989). These tests indicate that differences are statistically significant in all of the cases. For this reason we will continue discussing the performance of the models referring to their associated R^2's in the remainder of the article.

Table 3 Evaluation of the conditional CAPM with various measures of human capital returns.

Campbell measure						
Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	1.43	−0.43	0.25	0.28		60.02
t-value	5.37	−1.25	3.77	3.17		
(p-value)	(0.00)	(20.07)	(0.07)	(1.96)		
Estimate	2.01	−0.45	0.23	0.17	−0.09	66.92
t-value	5.17	−1.27	3.26	3.66	−1.60	
(p-value)	(0.00)	(18.98)	(0.11)	(1.48)	(10.21)	
Coefficient	δ_0	δ_{vw}	δ_{prem}	δ_{hk}		HJ-dist (p-value)
Estimate	2.51	1.73	−69.92	−87.26		0.5921 (43.23)
t-value	6.72	1.09	−3.46	−4.01		
(p-value)	(0.00)	(26.17)	(0.15)	(0.09)		
Shiller measure						
Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	1.36	−0.41	0.27	0.23		58.11
t-value	3.26	−1.22	3.60	2.07		
(p-value)	(0.00)	(21.12)	(0.08)	(2.97)		
Estimate	1.81	−0.41	0.22	0.12	−0.08	65.06
t-value	3.32	−1.23	3.17	2.21	−1.51	
(p-value)	(0.00)	(20.87)	(0.30)	(3.15)	(12.22)	
Coefficient	δ_0	δ_{vw}	δ_{prem}	δ_{hk}		HJ-dist (p-value)
Estimate	2.39	1.80	−68.26	−98.17		0.6091 (30.02)
t-value	5.82	1.17	−3.26	−3.00		
(p-value)	(0.00)	(23.23)	(0.12)	(0.28)		
Jagannathan–Wang measure[a]						
Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	1.24	−0.40	0.34	0.22		55.21
t-value	5.51	−1.18	3.31	2.31		
(p-value)	(0.00)	(23.76)	(0.09)	(2.07)		
Estimate	1.70	−0.40	0.20	0.10	−0.07	64.73
t-value	4.61	−1.18	3.00	2.09	−1.45	
(p-value)	(0.00)	(23.98)	(0.27)	(3.62)	(14.74)	
Coefficient	δ_0	δ_{vw}	δ_{prem}	δ_{hk}		HJ-dist (p-value)
Estimate	2.26	1.81	−65.72	−97.72		0.6184 (19.38)
t-value	6.39	1.26	−3.10	−2.94		
(p-value)	(0.00)	(20.65)	(0.20)	(0.33)		
R^I measure						
Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	1.66	−0.67	0.24	0.33		64.82
t-value	6.67	−0.34	4.15	4.01		
(p-value)	(0.00)	(52.21)	(0.01)	(0.93)		

continued

Table 3 (*continued*)

Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	2.62	−0.71	0.22	0.26	−0.09	69.33
t-value	6.06	−1.02	3.51	4.62	−1.58	
(p-value)	(0.00)	(40.07)	(0.09)	(0.50)	(9.68)	
Coefficient	δ_0	δ_{vw}	δ_{prem}	δ_{hk}		HJ-dist (p-value)
Estimate	2.60	2.06	−65.24	−83.62		0.5882 (50.09)
t-value	7.63	0.90	−4.01	−4.60		
(p-value)	(0.00)	(33.21)	(0.04)	(0.05)		
R^S measure						
Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	0.93	−0.37	0.36	0.16		39.92
t-value	4.82	−0.92	3.29	1.63		
(p-value)	(0.00)	(31.22)	(0.10)	(5.17)		
Estimate	1.81	−0.39	0.18	0.14	−0.09	63.02
t-value	5.11	−1.14	2.66	1.28	−1.38	
(p-value)	(0.00)	(25.11)	(1.17)	(8.82)	(14.22)	
Coefficient	δ_0	δ_{vw}	δ_{prem}	δ_{hk}		HJ-dist (p-value)
Estimate	1.62	2.17	−48.22	−73.22		0.6407 (3.81)
t-value	7.23	1.42	−2.62	−1.31		
(p-value)	(0.00)	(17.17)	(1.48)	(9.45)		
Becker–Mincer measure						
Coefficient	c_0	c_{vw}	c_{prem}	c_{hk}	c_{size}	R^2
Estimate	1.15	−0.11	0.43	0.14		34.21
t-value	4.92	−0.42	2.81	1.17		
(p-value)	(0.01)	(48.21)	(0.14)	(10.02)		
Estimate	1.72	−0.11	0.21	0.14	−0.14	62.50
t-value	5.38	−0.52	2.01	1.02	−0.92	
(p-value)	(0.00)	(44.11)	(4.81)	(14.21)	(21.22)	
Coefficient	δ_0	δ_{vw}	δ_{prem}	δ_{hk}		HJ-dist (p-value)
Estimate	2.21	2.14	−38.21	−102.21		0.6412 (3.43)
t-value	6.81	1.22	−2.17	−0.86		
(p-value)	(0.00)	(19.01)	(3.09)	(17.23)		

This table gives the estimates for the same cross-sectional regression model and the same moments model considered in Table 2. The regression models are estimated by using the Fama–MacBeth procedure. The models for the moments are estimated by using the GMM with the Hansen–Jagannathan weighting matrix. The minimized value of the GMM criterion function is the first item under "HJ-dist," with the associated p-value immediately below it.
[a]Source: Jagannathan and Wang (1996).

Table 4 Evaluation of the static CAPM with various measures of human capital returns.

Coefficient	δ_0	δ_{vw}	δ_{hk}	HJ-dist (p-value)
Campbell measure				
Estimate	1.51	1.10	−73.15	0.6392 (3.86)
t-value (p-value)	6.68 (0.00)	1.00 (32.17)	−3.21 (1.21)	
Shiller measure				
Estimate	1.47	1.17	−71.12	0.6417 (2.38)
t-value (p-value)	7.26 (0.00)	0.80 (43.17)	−2.50 (1.92)	
Jagannathan–Wang measure				
Estimate	1.37	1.22	−68.68	0.6422 (1.94)
t-value (p-value)	7.73 (0.00)	0.85 (39.65)	−2.32 (2.01)	
R^I measure				
Estimate	1.66	1.00	−82.17	0.6389 (5.17)
t-value (p-value)	6.17 (0.00)	0.73 (42.17)	−4.15 (0.82)	
R^S measure				
Estimate	1.14	1.30	−53.15	0.6483 (0.05)
t-value (p-value)	7.92 (0.00)	0.92 (36.12)	−2.11 (3.89)	
Becker–Mincer measure				
Estimate	0.98	1.41	−46.12	0.6501 (0.00)
t-value (p-value)	8.80 (0.00)	1.17 (32.41)	−1.96 (5.01)	

This table gives the estimates for the moments model $E[R_{it}(\delta_0 + \delta_{vw}R_t^{vw} + \delta_{hk}R_t^{hk})] = 1$. The return on portfolio i ($i = 1, 2, \ldots, 100$) in month t is denoted by R_{it}, R_t^{vw} is the value-weighted index of stocks, and R_t^{hk} is the aggregate return on human capital assets. The model is estimated by using the GMM with the Hansen–Jagannathan weighting matrix. The minimized value of the GMM criterion function is the first item under "HJ-dist," with the associated p-value immediately below it.

expected future labor income improves further the empirical performance of the model. These results indicate that labor market risks associated with these revisions in expectations may represent a relevant driving force for financial asset prices at the margin.

We turn to examining the performance of the conditional CAPM with the human capital measure $\mathcal{R}^I$ that accounts for capital gains, skills premia, and endogenous labor supply. Interestingly enough, the model performs *even better* than with the Campbell measure: the p-values for c_{hk}, c_{prem}, δ_{hk}, and δ_{prem} decrease with respect to those of the Campbell measure, the R^2 of the models (with and without portfolio size) is greater and, correspondingly, the HJ-dist statistic is smaller. The R^2 in the model without portfolio size is about 7% greater with $\mathcal{R}^I$ than with the Campbell measure, and thus about 17% greater (in relative terms) than for the growth rate in per capita labor income (64.82% versus 55.21%). The hypothesis that the value-weighted index of stocks is not part of the discount factor still cannot be rejected.

These strong results support the argument that aggregate labor market risks associated with marginal individual human capital gains, skill premia, and endogenous labor supply are an important source of cross-sectional variation in security prices. Given that these risks are fundamentally different than those associated with the Campbell measure and its special cases, these results provide a new perspective on the types of labor market risks that may be driving financial asset returns.[12]

We next examine the performance of the model in the case of $\mathcal{R}^S$. Of interest is that during our period of study, this measure remains essentially flat. The model in this case shows only a modest improvement with respect to the case in which human capital is ignored. The hypothesis that c_{hk} and δ_{hk} are zero cannot be rejected and the p-value of the HJ-dist statistic indicates that the pricing error is different from zero. This result indicates that there is very little informational content in an aggregate rate of return associated with the distribution of educational attainments. We conclude that the slow aggregate changes that take place in this distribution do not represent a relevant labor market risk that is priced in security returns, at least not at the monthly frequencies that we study.

Lastly, we examine the performance of the model with the Becker–Mincer measure. The results show that the performance is slightly worse than the poor performance obtained with the $\mathcal{R}^S$ measure.[13] As indicated earlier, this may be attributed to the fact that this average internal rate of return may not be interpreted as an individual marginal human capital return. Perhaps more importantly, the semilogarithmic form adopted in the literature is concerned with the average education or skill premium but it does not capture the capital gains or change in value of the existing stock of human capital.[14] Judging from the results obtained for $\mathcal{R}^I$, marginal individual returns and capital gains do appear to be important labor market risks driving security returns.

Finally, in Table 4 we examine the extent to which R_t^{hk} alone may be the driving force of the model by evaluating the static CAPM with the same measures of aggregate human capital returns for the model for the moments. The results

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[12] We also considered the closely related approach suggested by Buchinsky and Leslie (1997). These authors consider the basic finite-horizon dynamic optimization model with endogenous labor supply in the literature where individuals decide in each period their current consumption and whether to attend school or gain a year of work experience. The two basic differences with respect to the basic model in the literature are that the model considers evolving perceptions about future wages and that they use a quantile regression approach. The performance of the conditional CAPM with the Buchinsky–Leslie measure is very similar to the one obtained with the $\mathcal{R}^I$ measure. This result, which is available in Palacios-Huerta (2002), confirms the idea that capital gains and skill premiums are important labor market risks that drive security prices. Also, consistent with the slight differences between the Campbell and Shiller measures, this result means that evolving perceptions about future wages have a relatively small effect.

[13] Among all the measures considered, the hypothesis that the coefficient c_{hk} is zero is always rejected, except for the $\mathcal{R}^S$ and Becker–Mincer measures. The hypotheses that c_{prem} and δ_{prem} are zero are always rejected, while the hypothesis that c_{size} is zero is never rejected.

[14] Another potential problem with the semilogarithmic regression form adopted in hundreds of studies in the literature is that it is linear in schooling. Belzil and Hansen (2002) have recently estimated a structural dynamic programming model of schooling decisions and obtained that this function is convex in schooling.

show that the coefficient δ_{hk} is always strongly significant, while δ_{vw} is highly insignificant across the different human capital measures. However, the HJ-dist statistic is much greater than in the conditional CAPM in all cases, and in no case can the hypothesis that the pricing error is zero be accepted. These results indicate that in order to explain the cross-sectional variation of expected returns it is necessary to allow for time variations in betas.[15]

After two decades of important methodological progress in financial economics and the persistence of several puzzles in the field, some new models have been recently developed that incorporate a role for human capital and for labor income and labor market risks [e.g., Campbell (1996), Constantinides and Duffie (1996)]. The evidence in this section shows how the dynamic version of the CAPM that includes human capital can explain a great deal of the variability of financial asset returns in the United States. The main result of the analysis is that it identifies new, specific labor market risks that significantly increase the explanatory power of the conditional CAPM. Revisions in expected future labor income and financial asset returns have a modest but relevant effect. Labor market risks associated with marginal human capital gains and skill premia appear to be an important driving force of security returns.

3 EXTENSIONS AND CONCLUDING REMARKS

A number of extensions of the analysis have also been implemented. I briefly discuss some of them next.[16] First, the model was compared with factor models often employed in the literature. We added the four factors in Chen, Roll, and Ross (1986) to our conditional CAPM with human capital.[17] We found that none of them is ever significant for any of the human capital measures that we study, while both δ_{prem} and δ_{hk} are highly significant. Moreover, adding these factors decreases the HJ-dist statistic just slightly. The same basic result is obtained when adding the factor size and book-to-market studied in Fama and French (1993).[18] Neither size nor book-to-market are significant, while both δ_{prem} and δ_{hk} are highly significant. These results are relevant because these factors are often employed in important literature that is concerned with various risk management issues and in several empirical applications within the framework of asset pricing models.

[15] The cross-sectional regression model $E[R_{i,t}] = c_0 + c_{vw}\beta_{vw} + c_{hk}\beta_{hk}$ was also estimated. The results are consistent with these findings and the coefficients have the expected signs. The R^2's of the models are 43.24 (Campbell), 33.17 (Shiller), 43.66 ($\mathcal{R}^I$), 12.17 ($\mathcal{R}^S$), and 6.26 (Becker–Mincer).

[16] The results are available in Palacios–Huerta (2002), which also collects other extensions and refinements that are not discussed here such as (i) the role of ability and selectivity biases in the measurement of human capital returns, (ii) the effects of accounting for tuition costs in addition to foregone earnings in the cost of education, and (iii) estimates using the return to experience conditional on education. None of them seem to generate any new interesting results.

[17] These factors are the monthly return spread between the long-term government bond and the Treasury bill, the difference between the returns on long-term corporate bonds and long-term government bonds, monthly industrial production, and the change in inflation rate.

[18] The corresponding cross-sectional regression models also confirm these findings for both the Chen–Roll–Ross and Fama–French factors.

The performance of the model was also evaluated using the human capital returns of stockholders alone, rather than aggregate human capital returns. The differentiation between stockholders and nonstockholders has already been fruitful in the consumption-based asset pricing literature for explaining part of the equity premium puzzle. In principle, it may also turn out to be helpful here if the "relevant" wealth portfolio is that of individuals who participate in financial markets.[19] We find that the fit of the models improves across all the measures that we examine when the model is implemented using stockholders' human capital returns rather than aggregate human capital returns. This basic result lends support to the idea that the specific labor market risks associated with stockholders may be particularly relevant for understanding how investors assess risk and value risky cash flows.[20]

In summary, the analysis in this article represents an econometric application drawn from the interface between finance, labor economics, and macroeconomics within the framework of asset pricing models. It provides an empirical evaluation of the performance of the conditional CAPM with human capital using different approximations to aggregate human capital returns. The main contribution of the analysis is that we are able to identify new types of labor market risks that drive financial asset prices, especially marginal capital gains and skill premiums in human capital markets. Given the central role that this model has in the literature, these results may be valuable for risk management, evaluating how markets assess risk, testing within the context of asset pricing models, and for a number of applications in different fields.

Lastly, we have considered different human capital measures in order to avoid some of the shortcomings inherent in the growth rate in per capita labor income. Yet no single human capital measure is able to capture all the labor market risks that were studied in this article. This is a problem that has occupied and continues to occupy a central place in the labor economics literature. Uncovering and estimating the precise causal effect of investments in human capital in the labor market is an extremely difficult task. As the results in this article provide substantial support for the argument that human capital and labor market risks are among the main real macroeconomic risks that drive financial asset prices, it seems natural that future progress in the literature on estimating the economic returns to education should feed back to the empirical implementation of financial asset pricing models.

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[19] See, for instance, Mankiw and Zeldes (1991) and Vissing-Jørgensen (1997).

[20] We considered as stockholders individuals that are white males with at least a college degree, age 40 and older. Although this is the demographic group more likely to hold stocks in the PSID, CEX, and SCF surveys, this assumption may be problematic. Also, given that entrepreneurial risk may be strongly related to the specific human capital assets that stockholders hold, we examined the extent to which proprietary income has any relevant effects. We found that it is a significant factor that improves the perfomance of the model as well.

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