NBER WORKING PAPER SERIES

LABOR INCOME AND PREDICTABLE STOCK RETURNS

Tano Santos
Pietro Veronesi

Working Paper 8309
http://www.nber.org/papers/w8309

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2001

We thank Fernando Alvarez, Nick Barberis, John Y. Campbell, John H. Cochrane, George Constantinides, Kent Daniel, Gene Fama, Lars P. Hansen, John Heaton, Michael Johannes, Martin Lettau, Sydney Ludvigson, Lubos Pastor, and seminar participants at the 2000 NBER Summer Institute in Asset Pricing, Columbia University, Northwestern University and the University of Chicago. We thank Lior Menzly for excellent research assistance. Part of this research was conducted while the first author was enjoying the hospitality of the Graduate School of Business of Columbia University. All errors are our own. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

© 2001 by Tano Santos and Pietro Veronesi. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Labor Income and Predictable Stock Returns
Tano Santos and Pietro Veronesi
NBER Working Paper No. 8309
May 2001
JEL No. G1

ABSTRACT

We propose and test a novel economic mechanism that generates stock return predictability on both the time series and the cross section. In our model, investors' income has two sources, wages and dividends, that grow stochastically over time. As a consequence, the fraction of total income produced by wages changes over time de-pending on economic conditions. We show that as this fraction fluctuates, the risk premium that investors require to hold stocks varies as well. We test the main implications of the model and find substantial support for it. A regression of stock returns on lagged values of the labor income to consumption ratio produces statistically significant coefficients and adjusted R^2 's that are larger than those generated when using the dividend price ratio. Tests of the cross sectional implication find considerable improvements on the performance of both the conditional CAPM and CCAPM when compared to their unconditional counterparts.

Tano Santos
Graduate School of Business,
University of Chicago
and NBER
jesus.santos@gsb.uchicago.edu

Pietro Veronesi
Graduate School of Business,
University of Chicago,
NBER, and CEPR
pietro.veronesi@gsb.uchicago.edu

I. **INTRODUCTION**

Predictability, both in the time series and the cross section of stock returns, has been the focus of much research in the field of empirical finance. At the time-series level, the main finding is that variables like the price-dividend ratio and term premia can predict stock returns variation at long horizons.[1] As for the cross section of stock returns, predictability translates into the use of conditioning variables to improve on the performance of the CAPM and Consumption CAPM (CCAPM) versus their unconditional counterparts. These two strands of the literature connect because lagged instruments that are shown to predict market returns are natural conditioning variables for tests of the cross section.[2]

Extant economic explanations for the time-series and cross-sectional predictability are notably sparse and detached from one another. Time series predictability is obtained by either investors' learning about some unobservable fundamental process as in Timmermann (1993, 1996) and Veronesi (2000) or cyclical variations in investors' risk aversion as in Campbell and Cochrane (1999) and Barberis et al. (2001). Instead, at the cross-sectional level, the theoretical models concentrate either on portfolio constraints (Cuoco (1997)) or the exploitation of growth options' opportunities (Gomes et al. (2000)). A notable exception is Berk et al. (1999) who construct a model of firm's investment with implications for the cross section and that yields interest rates as predictors of market returns.

In this paper we propose and test a different economic mechanism that generates stock return predictability both at the time-series and at the cross-sectional level, namely, fluctuations in the fraction of consumption funded by sources other than dividends from the stock market. The intuition is straightforward. In addition to the dividends paid by competitively traded stocks, investors have an endowment flow of consumption good. As the fraction of consumption funded by this endowment fluctuates, the relationship between stock returns

[1] This evidence has survived a decade long effort to tackle many of the econometric issues that are relevant for evaluating these effects "at reasonable if not overwhelming levels of statistical significance," (Campbell (2000), page 9.) Furthermore, predictability is not unique to the standard US data set, but it can be found in many other countries as well (see Campbell (1999), Table 12, panel B). For a summary see Cochrane (1997 and 2000).

[2] See Cochrane (1996), Ferson and Harvey (1999), and Lettau and Ludvigson (2000b) for recent contributions in this direction. For example Ferson and Harvey (1999) state that "simple proxies for time variation in expected returns, based on common lagged instruments, are also significant cross-sectional predictors of returns."

and consumption growth varies as well, thereby generating changes in the risk premia investors require to hold stocks. Clearly some portfolios will be more sensitive than others to these fluctuations and as a consequence will demand different premia, generating the desired cross sectional predictability.

An obvious candidate for this additional source of consumption is labor income and it is to this interpretation that we restrict ourselves throughout the paper. Labor income, after all, accounts for more than 80% of total consumption on average and, as shown in Figure 1, varies between 75% and 90%. At the aggregate level it is rather intuitive that periods characterized by a high labor-income to consumption ratio should also imply a low expected excess return: Since most of consumption is not stemming from the stock market, investors do not need to require a high premium. A similar intuition holds at the cross-sectional level.

To formalize this intuition we write a minimal extension of the standard Lucas (1978) exchange economy to accommodate, in a tractable model, the possibility of multiple sources of consumption. In our set up investors receive both dividend income from many risky securities and "other income," such as labor income. By concentrating on the "fractions" of dividends and wages to consumption, and under conventional preferences, we can solve for stock prices in closed form and obtain simple formulas for stock returns. As mentioned, our first finding is that the ratio of labor income to consumption is the main determinant of the predictability of stock market returns because of the intuitive mechanism developed above. In addition, we also obtain a stochastic beta representation for the cross-section of stock returns as well as intuitive formulas for the "betas" themselves. These "betas" are indeed mainly affected by the labor income to consumption ratio with a sensitivity that is asset specific and depends on the characteristics of the underlying dividend process.

We test the main predictions of the model by running predictive regressions using both the ratio of labor income over total consumption and/or the dividend price ratio as explanatory variables. Our first main empirical finding is that for the overall sample 1946-1999 the ratio of labor income to total consumption performs much better than the (log) dividend price ratio to forecast future returns. For example, the R^2 of the one year predictive regression is 6.1% (against 3.9% for the log dividend-price ratio) and it reaches 34.6% for the four year ahead regression (against 20.7% for the dividend price ratio.) Since this result may be driven by the inclusion of the 1995-1999 period in the data sample (which witnessed a low dividend price ratio and high returns,) we also run regressions over the more conventional 1952-1994 data period where it is known that the dividend price ratio is working well (see e.g. Campbell et al. (1997)). In this case the dividend price ratio is performing better than the wages-to-consumption ratio, but the latter is still a significant regressor at long horizons where it still produces a good forecasting power: The R^2 is 3% for the one year ahead regression but it reaches 22.6% for the 4 year ahead regression.

Interestingly, the inclusion of both regressors – either linearly or in a multiplicative fashion – dramatically improves upon the predictive power of the regression at every horizon. For example, in the 1952-1994 sample the (adjusted) R^2 ranges between 25.1% at the one year horizon to above 60% at the four year horizon. This finding is indeed fully consistent with our model, which implies that both expected returns and the dividend yield are non linear functions of the labor income to consumption ratio. It follows that the dividend yield may proxy for the non linear relation between expected returns and this ratio and it is then not surprising that it improves the predictability.

The cross-sectional implications of the model, that is, the stochastic beta representation for the expected returns of individual securities, are investigated next. Roughly, we test whether conditioning the CAPM and the CCAPM by the share of labor income to consumption improves the fit on the cross section relative to their unconditional counterparts.

To test these hypothesis we use a set of portfolios that has become standard in the literature, the 25 Fama and French (1992, 1993) portfolios, which are portfolios sorted by size and book to market. A novel feature though is that we use a longer sample period than the one originally used by these two authors and others after them. Whereas the standard sample period is 1963-1998 in this paper we use the 1946-1998 period, but we also report results in the more restricted sample.

As many have noted before us, the standard CAPM explains little of the cross sectional variation in stock returns. The adjusted R^2 is only 10%, that is, the unconditional CAPM can only explain 10% of the cross sectional variation in returns. In contrast the inclusion of the returns on the market portfolio scaled by the fraction of labor income to consumption considerably increases the explanatory power of the CAPM. In this case the adjusted R^2 is 43%. We show that this cross term is significant and it's relevance robust to several specifications. Furthermore when the fraction of labor income to consumption enters independently the adjusted R^2 is as a high as 61%, a notable improvement over unconditional versions of the model.

We test whether the results are present in the more standard period of 1963-1998. They are. In this case the specification suggested by our model can explain as much as 54% of the cross sectional variation in returns whereas the unconditional CAPM explains a puny -2%.

We also test whether our specification is robust to the "dating convention" advocated by Jagannathan and Wang (1996) which provides investors with an information set consistent with the release of data by the Bureau of Economic Analysis. In an environment where human capital is a tradable asset investors need to know it's price in order to form their optimal portfolio. Jagannathan and Wang (1996) argue that that it is not reasonable to assume that investors posses information on data collected by the BEA and that is released with delay. Our results are robust to this dating convention. Furthermore we show that the role of labor income growth in tests of the cross section as a proxy for human capital returns depends critically on the dating convention adopted by the researcher.

Because this paper shows evidence pertaining to both the time series of the aggregate market and the cross section of stock returns it naturally relates to the two strands of the empirical asset pricing literature that have respectively dealt with these two issues. Our work though presents important differences with these two bodies of evidence.

First, the early predictability literature documents the forecasting power of either prices scaled by dividends or earnings and of various interest rate measures.[3] More recently Lettau and Ludvigson (2000a) (LLa henceforth) manipulate the budget constraint to show that the consumption to total wealth ratio, which includes labor income and financial wealth, contains information about stock returns.

Our paper adds to this literature by providing yet more evidence on the predictability of stock returns. A critical difference between our work and previous empirical research though is the fact that our predictive variable is neither a version of the stock price scaled by either dividends or earnings nor some other financial variable like the term premium, but rather a pure macroeconomic variable. Furthermore, it does not need to be estimated as in LLa as it is directly observable. Finally it is important to emphasize that our testable implication does not result from basic manipulations of either the definition of returns (Cochrane (2001), page 395-6) or the budget constraint as in LLa.

Second, the present paper adds to a literature that emphasizes the role of labor income in the cross section of stock returns. References on human capital and asset returns go as

[3]Campbell and Shiller (1988a and b), Fama and French (1988a and b), Hodrick (1992), Lamont (1998) document the predictive power of prices scaled by dividends and earnings. Campbell (1987), Fama and French (1989), Hodrick (1992), and Keim and Stambaugh (1986) show the forecasting power of interest rate measures.

far back as Mayers (1972) and Fama and Schwert (1977) and, more recently, authors like Jagannathan and Wang (1996) and Campbell (1996) have included human capital returns to improve on the definition of the market portfolio. For instance, in tests of the cross section, Jagannathan and Wang (1996) find that the inclusion of human capital in the definition of the market portfolio considerably improves the ability of the CAPM to explain the cross section of portfolios sorted by size and beta.

In a different direction Lettau and Ludvigson (2000b) (LLb henceforth) explicitly model the discount factor as a function of current information and show that the ratio of consumption to total wealth, a variable shown to predict market returns in LLa, is an important instrument for tests of the conditional CAPM and CCAPM. In particular they show that their version of the conditional CAPM and CCAPM provides a remarkable fit to the 25 Fama and French (1993) portfolios.

As already emphasized our conditioning variable is not a version of the price scaled by any other variable, whether it be earnings, dividends, or consumption itself. In this sense it is free from the concerns advanced by Berk (1995), namely, that because returns are mechanically related to prices, ratios that have prices either in the numerator or denominator are in turn automatically related to returns. For this reason these ratios cannot identify whether they correlate with the cross section because they proxy for economically meaningful forces or some other reason, like misspricing effects.

We close this introduction by pointing out that our framework does not attempt to resolve other long standing issues in the field of empirical asset pricing, such as the equity-premium puzzle or the risk-free rate puzzle. Rather, it illustrates how alternative sources of income other than dividends may have a role to play in accounting for the empirical properties of stock return data. As a consequence, and to offer a clear picture of the economic forces at work in our set up, we depart from the recent trend of investigating alternative preference specifications to match the moments of stock and bond returns to focus on the well known iso-elastic case. Clearly a full account of empirical properties of returns require additional ingredients like variation in the investors attitudes towards risk, as in Campbell and Cochrane (1999) or Barberis, Huang, and Santos (2001) but we do not attempt such a comprehensive exercise here.

Section II contains the model and discussion of the assumptions. Section III provides the results that motivate our empirical strategy. Data description and the empirical results are reported in section IV. Section V concludes. Proofs, tables, and figures are in the appendix.

II. THE MODEL

Consider a standard pure exchange economy populated by identical investors whose utility function is[4]

$$U(C_t, t) = e^{-\phi t} \log(C_t),$$

where C_t denotes consumption at time t. There is a riskless asset in zero net supply that pays a continuous rate of return r_t. There are $n-1$ risky assets in positive net supply that pay a continuous dividend rate D_t^i for $i = 2, 3, , \ldots, n$, and that trade competitively at a price P_t^i. Agents are endowed with an additional source of income other than dividends from these competitively traded financial assets. In accordance with our empirical strategy below, we assume that this other income springs from a human capital asset that pays a continuous wage rate w_t.[5] For ease of notation we will sometimes denote w_t by D_t^1.

The problem of the investor is then the usual one:

$$\max_{N_t^i, C_t} E_0 \left[\int_0^\infty U(C_t, t) dt \right]$$

subject to the standard dynamic budget constraint

$$dW_t = \sum_{i=2}^{n} N_t^i \left(dP_t^i + D_t^i dt \right) + \left(W_t - \sum_{i=2}^{n} N_t^i P_t^i \right) r_t dt + (w_t - C_t)\, dt,$$

where N_t^i denotes the number of shares of stock i held by the investor and W_t is his total wealth at time t.

A rational expectations equilibrium is then a set of price functions P_t^i, allocation process N_t^i, and consumption process C_t such that agents maximize and markets clear, that is, $N_t^i = 1 \quad \text{for all} \quad i = 2, 3, \ldots, n \quad \text{and} \quad C_t = w_t + \sum_{i=2}^{n} D_t^i$.

As already mentioned, our emphasis is on the general payoff structure available to the investor rather than the more traditional concerns on preferences. A basic requirement in modeling this general payoff structure is that dividends and wages add up to an aggregate consumption process that is consistent with the observed behavior of the US time series, which is roughly a random walk. Once this requirement is met, the proposed endowment structure will also naturally embed the standard endowment economy of Lucas (1978).

[4] In appendix we extend these results to the general CRRA case.

[5] A fully rigorous account of labor income in an asset pricing framework should accommodate the endogenous labor supply decision. We abstract from this effect in the present paper.

We start then by modeling consumption growth as

$$\frac{dC_t}{C_t} = \mu_c dt + \sigma_c d\mathbf{B}_t, \tag{1}$$

where μ_c is a scalar and σ_c is a $1 \times n$ vector of constants and $\mathbf{B}_t = (B_t^1, \ldots, B_t^n)'$ are n independent Brownian motions. The specification of μ_c is flexible and in particular it can be time varying to reflect any weak autocorrelation in consumption growth that may be observed in the data.

In order to model dividends and wages define first the *share* of these dividends and wages over consumption:

$$s_t^w = s_t^1 = \frac{w_t}{C_t} \quad \text{and} \quad s_t^i = \frac{D_t^i}{C_t} \quad \text{for} \quad i = 2, ..., n, \tag{2}$$

By construction then wages and dividends will add up to the consumption process in (1) if $\sum_{j=1}^n s_t^j = 1$. To illustrate the economic forces at work we propose a simple process for the share dynamics and leave for the appendix the description of a richer, but equally tractable, model. In particular we assume that:

$$ds_t^i = a\left(\overline{s}^i - s_t^i\right) dt + s_t^i \sigma_i\left(\mathbf{s}_t\right) d\mathbf{B}_t \tag{3}$$

where

$$\sigma_i\left(\mathbf{s}_t\right) = \nu_i - \sum_{j=1}^n s_t^j \nu_j, \tag{4}$$

ν_i for $i = 1, 2, \ldots, n$ are n dimensional vectors, and $\mathbf{s}_t = (s_t^1, \ldots, s_t^n)$. Our choice for the functional form of the volatility function (4) guarantees that both $s_t^i > 0$ and $\sum_{i=1}^n s_t^i = 1$.

We model then these shares as a mean reverting process with a common reversion speed, a, and conditional expected value given by

$$E_t\left[s_\tau^i\right] = \overline{s}^i + \left(s_t^i - \overline{s}^i\right) e^{-a(\tau - t)}. \tag{5}$$

If a particular "tree" is contributing little to consumption compared to its unconditional level, as expressed by it's low s_t^i, then one should expect a high positive growth rate of this share. In the future a larger percentage of consumption will come from asset i.

But, as it is intuitive, what is critical in the valuation of any of the available assets is whether on average they grow when consumption does. It can be easily shown that the covariance between consumption growth and share growth is given by

$$cov_t\left(\frac{ds_t^i}{s_t^i}, \frac{dC_t}{C_t}\right) = \theta_i - \sum_{j=1}^{n} s^j \theta_j \tag{6}$$

with $\theta_i = \nu_i \sigma_c'$. The parameters θ_i's, that regulate the covariance between consumption growth and the growth of the share of consumption produced by asset i, will play an important role in the formula for asset returns, and for this reason we elaborate on them further.

First, equation (6) shows that the constants θ_i are not identified as we can add a constant to all of them without changing any of the covariances. For this reason we can renormalize them and we find it convenient to set $\theta_1 = 0$. Second, since the fraction of consumption generated by wages s_t^w is by far the largest component of all s_t^i's, it is convenient to find a an expression for the covariance in (6) that makes explicit the dependence on s_t^w. By substituting the identity $s_t^i = 1 - \sum_{j \neq i} s_t^j$ in equation (6) and rearranging terms we immediately find that

$$cov_t\left(\frac{ds_t^i}{s_t^i}, \frac{dC_t}{C_t}\right) = s_t^w \theta_i + \sum_{j \neq 1, i} s_t^j \left(\theta_i - \theta_j\right) \tag{7}$$

We use equations (6) and (7) repeatedly throughout.

III. RESULTS

In this section we describe the asset pricing implications of the model introduced in the previous section. We derive first the equilibrium price dividend ratios for both individual assets and the market portfolio. Then we explore the implications for the market asset returns and the cross section of stock returns.

III.A Equilibrium prices

In our set up, as in others, labor income is a tradable asset[6] and we abstract from any effect that market incompleteness may have on asset prices. For this reason the standard asset pricing formula applies:

$$P_t^i = E_t\left[\int_t^{\infty} \frac{U_c\left(\tau, C_\tau\right)}{U_c\left(t, C_t\right)} D_\tau^i d\tau\right]. \tag{8}$$

[6] See Campbell (1996) for example. For a lucid defense of this assumption see also Jagannathan and Wang (1996, page 13).

Given our assumptions on preferences and dividends, $U_c(\tau, C_\tau) = e^{-\phi\tau} C_\tau^{-1}$ and $D_\tau^i = s_\tau^i C_\tau$, equilibrium prices are:

$$P_t^i = E_t\left[\int_t^\infty e^{-\phi(\tau-t)} \frac{C_t}{C_\tau} s_\tau^i C_\tau d\tau\right] \quad (9)$$
$$= C_t \int_t^\infty e^{-\phi(\tau-t)} E_t\left[s_\tau^i\right] d\tau \quad (10)$$
$$= C_t \left\{\frac{a\overline{s}^i}{\phi(a+\phi)} + \frac{s_t^i}{a+\phi}\right\}, \quad (11)$$

where[7] we used equation (5). The expression for the price dividend ratio of asset i now follows trivially from equation (11):

$$\frac{P_t^i}{D_t^i} = \left(\frac{1}{\phi}\right)\left(\frac{1}{\phi+a}\right)\left[\phi + a\left(\frac{\overline{s}^i}{s_t^i}\right)\right]. \quad (12)$$

That is, the price-dividend ratio of asset i depends on the share of consumption that the representative consumer derives from asset i. In addition, the price dividend ratio of security i depends on the "distance" of its current level s_t^i from its long-run average $\overline{s}^i$.

Equation (12) extends naturally to the price dividend ratio of the market portfolio. Define $P_t^M = \sum_{i=2}^n P_t^i$ and $D_t^M = \sum_{i=2}^n D_t^i$. Then it is straightforward to show that:

$$\frac{P_t^M}{D_t^M} = \left(\frac{1}{\phi}\right)\left(\frac{1}{\phi+a}\right)\left[\phi + a\left(\frac{1-\overline{s}^w}{1-s_t^w}\right)\right] = \left(\frac{1}{\phi}\right)\psi(s_t^w) \quad (13)$$

Equation (13) has a strong intuitive appeal. The first term of the expression, $\frac{1}{\phi}$, is the standard price dividend ratio in one endowment economy with log utility function. The second term, $\psi(s_t^w)$, corrects for the presence of an alternative source of income other than dividends from the market portfolio.

Notice that $\psi(s_t^w) = 1$ only if $\overline{s}^w = s_t^w$. That is an economy in its steady state yields a price dividend ratio that is no different than the usual one. Deviations form this steady state generate movements in the price dividend ratio of the market portfolio. For instance, if $\overline{s}^w < s_t^w$ then the price dividend ratio is higher than it's long run level, $\frac{1}{\phi}$. There are two reasons for this. First, if s_t^w is relatively high investors are less exposed to fluctuations in the stock market, and hence they require a lower compensation to hold it, and this, in turn,

[7] The inversion of integrals between (9) and (10) is possible because $\phi > 0$ and $s_\tau^i \in [0, 1]$.

translates into higher prices. Also, a high share of labor income to consumption signals that future aggregate dividend growth is going to be above that of consumption as s_t^w will mean revert to $\overline{s}^w$. This further reinforces the positive effect on the price dividend ratio.

Equation (13) then captures an alternative source of variation in the price dividend ratio to the ones that have been emphasized in the literature.[8] As the share of labor income to consumption ratio varies the price dividend ratio will vary unambiguously. In the next section we explore whether the intuition carries to the aggregate market returns.

III.B Market returns

The excess stock returns of the market portfolio, dR_t^M, is defined as:

$$dR_t^M = \frac{dP_t^M + D_t^M dt}{P_t^M} - r_t,$$

where the risk free rate can be easily proved to be equal to:[9]

$$r_t = \phi + \mu_c - \sigma_c \sigma_c'.$$

In appendix we show that a straightforward application of Ito's lemma together with the fact that $E_t\left[dR_t^M\right] = cov_t\left(dR_t^M, \frac{dC_t}{C_t}\right)$ yields the following expression for the expected excess return of the market portfolio:

$$E_t\left[dR_t^M\right] = \sigma_c \sigma_c' + \frac{1}{1+\left(\frac{a}{\phi}\right)\left(\frac{1-\overline{s}^w}{1-s_t^w}\right)}\left(\frac{s_t^w}{1-s_t^w}\right)\sum_{j=2}^{n} s_t^j \theta_j. \tag{14}$$

In the standard "one tree" economy the conditional expected excess return of the market portfolio is simply $\sigma_c \sigma_c'$. Whether the level of the conditional expected excess return is above or below this benchmark depends on the covariance between wage income share growth and consumption growth, which, from equation (6), equals $-\sum_{j=1}^{n} s_t^j \theta_j$ (recall that $\theta_1 = 0$.) If this covariance is negative, then the premium is higher than in the standard case as the market tends to pay in the presence of consumption growth. If on the other hand the covariance is positive the expected excess return is lower than $\sigma_c \sigma_c'$ as the market provides a natural hedge against weak consumption growth.

[8] For instance Campbell and Cochrane (1999) emphasize changes in the degree of risk aversion as a source of variation.

[9] Recall that we allow for time varying μ_c and hence the dependence of the risk free rate on time. If μ_c is constant consumption growth is completely i.i.d.

As equation (14) shows, there are two sources of variation in expected excess returns: changes on the distribution of dividends across the market portfolio and fluctuations in s_t^w. What is the economic intuition behind each source of variation?

To gain some insights on the impact of cross sectional variation in the distribution of dividends across the market, $\sum_{j=2}^n s_t^j \theta_j$, assume that the share of labor income to consumption, s_t^w, stays constant and that we "redistribute" an amount δ away from share s_t^i to share s_t^j. Then the change in conditional expected excess return is given by:

$$\begin{aligned}\Delta E_t\left[dR_t^M\right] &= \delta\left(\frac{s_t^w}{(1-s_t^w)+\left(\frac{a}{\phi}\right)(1-\overline{s}^w)}\right)[\theta_j-\theta_i] \\ &= \delta\left(\frac{s_t^w}{(1-s_t^w)+\left(\frac{a}{\phi}\right)(1-\overline{s}^w)}\right)\left[cov_t\left(\frac{ds_t^j}{s_t^j},\frac{dC_t}{C_t}\right)-cov_t\left(\frac{ds_t^i}{s_t^i},\frac{dC_t}{C_t}\right)\right],\end{aligned}$$

where the last equality follows from equation (6). The expected rate of return of the market portfolio will rise if the covariance of asset j is higher than that of asset i. This is only natural, as dividends are redistributed towards the asset whose share growth covaries more strongly with consumption growth and hence the overall market is more strongly correlated with consumption growth.

Variations in the share of labor income to consumption is the second source of fluctuations in expected market returns. Unlike before though, it is not possible now to hold distributional effects fixed, as changes in s_t^w necessarily result in changes in $\sum_{j=2}^n s_t^j \theta_j$. An example then could be helpful here.

Assume that $\theta_j = \theta$ for all $j = 2, 3, \ldots, n$, that is, that the share growth rates have the same covariance with consumption growth. In this case, $\sum_{j=2}^n s_t^j \theta_j = \theta(1-s_t^w) = -cov_t\left(\frac{ds_t^w}{s_t^w},\frac{dC_t}{C_t}\right)$ (from (6)) which we can substitute into (14) to obtain

$$E_t\left[dR_t^M\right] = \sigma_c\sigma_c' + \frac{\theta s_t^w(1-s_t^w)}{\phi(1-s_t^w)+a(1-\overline{s}^w)} \tag{15}$$

Equation (15) shows that the instantaneous expected return depends non-linearly on the fraction of consumption produced by labor income $s_t^w = w_t/C_t$. Its functional form shows that expected returns are equal to $\sigma_c\sigma_c'$ both when $s_t^w = 0$ and when $s_t^w = 1$. To understand this result, notice that when $s_t^w = 0$, then $C_t = \sum_{j=2}^n D_t^j = D_t^M$ and hence we are in the usual Lucas (1978) economy with no other endowment than the risky assets. The results that in the log utility case $E_t\left[dR_t^M\right] = \sigma_c \sigma_c'$ is indeed standard. More puzzling at first is that this model implies that $E_t\left[dR_t^M\right] = \sigma_c \sigma_c'$ when $s_t^w = 1$. In this case we must have $s_t^i = 0$ for all $i = 2, .., n$ which from (11) entails $P_t^M = C_t \frac{a(1-\bar{s}^w)}{\phi(a+\phi)}$. Since we would also have $C_t = w_t$, we obtain that the price is perfectly correlated with wages (and hence consumption), yielding the result. Of course, both these limit cases are extreme, given that, as shown in Figure 1, s_t^w lies comfortably in the interval $(0.75, 0.9)$. In this case, what is the relationship between $E_t\left[dR_t^M\right]$ and s_t^w? In the simplified example of equation (15) where $\theta_j = \theta$ for all $j = 2, 3, \ldots, n$, we can see that the denominator of the second term is always positive, hence the behavior of expected stock returns depend on the sign of θ. To gain intuition on the likely sign of this term, recall again that $s_t^w (1 - s_t^w)\, \theta = -cov\left(ds_t^w, dC_t/C_t\right)$. If wages are much smoother than dividends, we can imagine that an increase in dividends is accompanied by an increase in consumption and hence a decrease in $s_t^w = w_t/C_t$ (if wages do not move much). This induces a natural negative covariance between consumption growth and the changes in s_t^w. Indeed, evidence (not reported) shows a negative covariance between ds_t^w and dC_t/C_t. Since $s_t^w (1 - s_t^w)$ is positive, this implies $\theta > 0$. This in turn yields a negative relationship between expected returns and the labor share s_t^w when s_t^w is in the relevant range $(0.75, 0.9)$. The economic intuition of this result is clear: as s_t^w increases, consumption becomes fueled by labor income only, decreasing the covariance between consumption growth and dividend growth. This in turn translates into a lower covariance between consumption growth and returns, generating a lower risk premium.

III.C The cross section of stock returns

Similar arguments to the ones used in the previous section yield a closed form solution to the conditional expected rate of return of asset i. Let $P_t^{TW} = P_t^M + P_t^w$ the value of the total wealth portfolio, that is, the portfolio that comprises the value of the market portfolio P_t^M and the value to human capital P_t^w. Notice that the latter can be computed from equation (11) for $i = 1$. If we denote by dR_t^{TW} the excess return from the total wealth portfolio, standard equilibrium conditions require $E_t\left[dR_t^i\right] = cov_t\left(dR_t^i, dR_t^{TW}\right)$ which in turns implies the "beta" representation

$$E_t\left[dR_t^i\right] = \beta_i\left(\mathbf{s}_t\right) E_t\left[dR_t^{TW}\right], \tag{16}$$

where the conditional beta $\beta_i\left(\mathbf{s}_t\right) = cov_t\left(dR_t^i, dR_t^{TW}\right)/var_t\left(dR_t^{TW}\right)$ can be written explicitly as a function of s_t^w and s_t^j's as:

$$\beta_i(\mathbf{s}_t) = 1 + \left(\frac{\theta_i}{\sigma_c \sigma_c' \left(1 + \frac{a}{\phi}\left(\frac{\overline{s}^i}{s_t^i}\right)\right)} \right) s_t^w + \left(\frac{1}{\sigma_c \sigma_c' \left(1 + \frac{a}{\phi}\left(\frac{\overline{s}^i}{s_t^i}\right)\right)} \right) \sum_{j \neq 1,i} s_t^j (\theta_i - \theta_j) \tag{17}$$

The conditional beta of each asset i with respect to the total wealth portfolio depends on both the share of labor income to consumption s_t^w and on the distribution of shares across the stock market $\sum_{j\neq 1,i} s_t^j$. The coefficients on each of this common "factors" depend on the relative position of s_t^i with respect to its steady state value, $\overline{s}^i$. For instance, in the case where $\theta_i = \theta$ for all $i = 2, 3, \ldots, n$, $\beta_i(\mathbf{s}_t)$ varies as a function of just s_t^w and s_t^i (the second term in (17) vanishes). The reason for this is as follows: In this case we recall that $cov_t\left(\frac{ds_t^i}{s_t^i}, \frac{dC_t}{C_t}\right) = \theta s_t^w$. If $\theta > 0$, conditional on s_t^i, an increase in s_t^w results in a higher conditional expected rate of return as a result of the increase of the covariance between consumption growth and share growth. The degree to which changes in s_t^w affect the beta $\beta_i(\mathbf{s}_t)$ of asset i depends also on the value of s_t^i. If $s_t^i \approx 0$ changes in s_t^w do not affect the required return, as asset i does not contribute to consumption and does not covary with its growth.

Given that the return on the total wealth portfolio is not directly observable, from (16) we obtain a formulation more suitable for the empirical analysis. Define first:

$$\Phi(\mathbf{s}_t) = \frac{P_t^w}{P_t^w + P_t^M},$$

where $\mathbf{s}_t = (s_t^1, s_t^2, \ldots, s_t^n)$, and again P_t^w is the price of the human capital asset. Then the return on the total wealth portfolio is given by:

$$dR_t^{TW} = \Phi(\mathbf{s}_t) dR_t^w + (1 - \Phi(\mathbf{s}_t))\, dR_t^M, \tag{18}$$

where dR_t^w is the rate of return on the human capital asset. Given that $E_t\left[dR_t^i\right] = cov_t\left(dR_t^i, dR_I^{TW}\right)$ we can use the definition of the return on the total wealth portfolio, equation (18), to obtain:

$$E_t\left[dR_t^i\right] = \Phi(\mathbf{s}_t) cov_t\left(dR_t^i, dR_t^w\right) + (1 - \Phi(\mathbf{s}_t))\, cov_t\left(dR_t^i, dR_t^M\right). \tag{19}$$

Then equation (19) implies that the conditional expected rates of return on both the human capital asset and the market are given by:

$$\left[E_t\left[dR_t^w\right] \quad E_t\left[dR_t^w\right]\right]' = \Sigma^{wM} \left[\Phi(\mathbf{s}_t) \quad (1 - \Phi(\mathbf{s}_t)\right]', \tag{20}$$

where Σ^{wM} as the variance-covariance matrix of dR_t^w and dR_t^M. From equation (20) we can get an expression for $[\Phi(\mathbf{s}_t) \quad (1-\Phi(\mathbf{s}_t)]'$ that we can readily substitute back into (19) to obtain the beta representation:

$$E_t\left[dR_t^i\right] = \beta_{iw}(\mathbf{s}_t)E_t\left[dR_t^w\right] + \beta_{iM}(\mathbf{s}_t)E_t\left[dR_t^M\right], \tag{21}$$

where $\beta_{iw}(\mathbf{s}_t)$ and $\beta_{iM}(\mathbf{s}_t)$ are the multiple regression coefficients:

$$[\beta_{iw}(\mathbf{s}_t) \quad \beta_{iM}(\mathbf{s}_t)]' = \left(\Sigma^{wM}\right)^{-1} \times \left[cov_t\left(dR_t^i, dR_t^w\right) \quad cov_t\left(dR_t^i, dR_t^M\right)\right].$$

Versions of equation (21) have been the focus of much research lately. For instance, Jagannathan and Wang (1996) test a version the above equation where they also extend the definition of the market portfolio to include returns in human capital and where their conditioning variable is the properly defined default premium, shown to forecast business cycles. More recently LLb have tested a similar equation in a different set of test portfolios where the conditioning variable is the consumption to wealth ratio, a conditioning variable that they show predicts future market returns.

Our version of the conditional CAPM has the advantage of unambiguously specifying the set of conditioning variables that could improve the performance of the conditional CAPM and CCAPM, namely, the shares of dividends and wages over consumption. We return below to the question of how to derive a specific test of our model.

We can derive along very similar lines the conditional Consumption CAPM which is given by:

$$E_t\left[dR_t^i\right] = \beta_{1i}^c\left(\mathbf{s}_t\right)dt + \beta_{2i}^c\left(\mathbf{s}_t\right)E_t\left[\frac{dC_t}{C_t}\right] \tag{22}$$

where $\beta_{1i}^c(\mathbf{s})$ is a function of $\mathbf{s}_t$ and $\beta_{2i}^c(\mathbf{s})$ is the regression coefficient of dR_t^i onto dC_t/C_t. As before we delay the specific test on this model to the empirical section.

What is the intuition behind these results? Recall that we have established earlier that movements in the share of labor income to consumption together with variation in the distribution of shares across the market result in variations in the conditional expected rate of return on the market portfolio. These changes are likely to affect alternative portfolios differently as they will display varying sensitivities to the share of labor income to consumption for example. This is what provides a role for this variable in tests of the cross section of stock returns.

IV. EMPIRICAL TESTS

In this section we test the main predictions of our model. We start by providing a brief description of the data set employed. We then test the implications for the time series behavior of the aggregate market portfolio. Last we explore whether our version of the conditional CAPM and CCAMP provides a better description of the cross section of stock returns.

We emphasize that in what follows we concentrate in the role of the share of labor income to consumption, s_t^w, as a predictive and conditioning variable and leave the effects of the cross sectional distribution of dividend shares for future research. There are two main reasons for this. We are interested in the role of labor income, a variable that has proved to play a considerable role in recent asset pricing tests (Jagannathan and Wang (1996), LLa and LLb,) and that seems a clear first order effect given the large percentage of consumption it funds. Another reason is our emphasis in bringing in conditioning information that is "purely" non financial as it provides a sharper view on the links between macroeconomics and financial markets.

IV.A Data description

The financial data we use is standard. We consider returns on the value weighted CRSP index, which includes NYSE, AMEX, and NASDAQ, as our measure of financial asset returns. Dividend price ratios are also obtained from CRSP and the risk free rate is the 90-day Treasury bill.

For both consumption and labor income we use data from the National Income and Product Accounts (NIPA). Following the literature (see LLa), we define consumption as nondurable plus services excluding shoes and clothing. The argument behind this idea is that the theory applies to the flow of consumption and it should not include additions or replacements to the stock of durable goods. As it is also traditional we assume that total consumption is proportional to consumption of non durables plus services and we choose a constant of proportionality to be the long term ratio between total consumption and consumption of non durables plus services. This ratio is estimated to be 1.15.

The labor income series is as in LLa. It is constructed by adding to wages and salaries, transfer payments plus other labor income and subtracting personal contributions to social insurance and taxes.[10] Both the consumption and labor income series are quarterly.

[10]See LLa Appendix A. As of the writing of this paper, data from 1929 to 1945 was still being revised by

For the cross sectional tests we use the sets of test portfolios constructed by Fama and French (1993). These portfolios are formed by intersecting 5 portfolios sorted by size with other five portfolios sorted by book-to-market. We convert the returns to quarterly data producing a time series covering 1946 to 1998.

IV.B Predictability of aggregate returns

IV.B.1 Forecasting regressions

We test first the forecasting power of the ratio of labor income to consumption. Recall that the main prediction of our model postulates that the high share of labor income to consumption, s_t^w, predicts low future returns. For this reason we run regressions of returns on lagged values of s_t^w. We also rerun the standard predictability regression to check its performance during our sample period and frequency. Finally we run two additional regressions that try to asses whether the role of the share of labor income to consumption in the predictability regression is robust to the inclusion of the price dividend ratio. That is we estimate:

$$r_{t,t+K} = \alpha_1 + \beta_1(K)s_t^w + \varepsilon_{t+k} \tag{23}$$

$$r_{t,t+K} = \alpha_2 + \beta_2(K)\log\left(\frac{D_t^M}{P_t^M}\right) + \varepsilon_{t+k} \tag{24}$$

$$r_{t,t+K} = \alpha_3 + \beta_3(K)\log\left(\frac{D_t^M}{P_t^M}\right) + \beta_4(K)s_t^w + \varepsilon_{t+k} \tag{25}$$

$$r_{t,t+K} = \alpha_5 + \beta_5(K)\left(s_t^w \times \log\left(\frac{D_t^M}{P_t^M}\right)\right) + \varepsilon_{t+k} \tag{26}$$

where $r_{t,t+K}$ is the cumulative log return over K periods. For each regression, Tables II-IV report the point estimate of the included explanatory variable, the Newey-West corrected $t-$statistic for the null hypothesis that the coefficients are zero, and the adjusted R^2.

We start discussing our results for the whole sample period at our disposal, 1946-1999. The first row of Table II-A shows that the ratio of labor income to consumption s_t^w is statistically significant at any forecasting horizons between one quarter and four years. The sign of the regression coefficient is negative, giving support to the view expressed in the previous section that positive innovations in s_t^w lead to low future returns. The explanatory power is also high, ranging from 6.1% for the one year regression to 34.6% for the four year

the Bureau of Economic Analysis. For an update visit, *http://www.bea.doc.gov.* See also footnote 11.

regression.

We compare these results with those of the standard predictability regression, equation (24). In this case, the dividend price ratio is never significant at any horizons and the predictive power is rather low, ranging from 3.9% at the one year horizon to 20.7% at the four year horizon. As we will see below, this poor performance of the dividend-price ratio to forecast future returns is partly due to the inclusion of the period 1995-1999 in the data sample. Indeed, during this period the dividend price ratio was extremely low and yet returns have been record high.

Recall that, as shown in equation (13), the dividend price ratio is a non linear function of s^w. Including the dividend price ratio then may proxy for any non linearities in the relation between returns and s^w. When both ratios enter linearly (regression (25)) both regressors are significant and the predictive power ranges from an adjusted R^2 of 16.2% at the one year horizon to an R^2 of over 61% at the four year horizon. Interestingly, a similar result obtains when we only use the interaction factor $s^w \times \log(D/P)$ in the regression (regression (26)). In this case again the coefficient is highly significant and the R^2 ranges from 13.4% at the one year horizon to over 50% at the four year horizon.

As shown in Figure 1, the first two years of our sample, 1946-7, showed a remarkable drop in the ratio of labor income to consumption. The special circumstances of those years may account for that event. We reran the predictability regression excluding those eight initial data points and we report the results in Table II-B. The short term predictability of our variable improves slightly but overall the estimates are very similar.

Other researchers using quarterly data, like LLa, concentrate on the period starting in 1952. In order to check the validity of our empirical findings, Tables III and IV report results for two subsamples of the data starting in 1952.[11] The first is the standard sample 1952:01-1994:04, that will enable us to compare our results to others in the literature.[12] Indeed the second line in Table III shows that during this period the dividend price ratio was doing

[11] We point out that the main result of this paper (that the labor income to consumption ratio forecast future returns) accidentally underwent an out-of-sample test. Until April 26th, 2000 data on compensation of employees and other series from the Bureau of Economic Analysis were only available for the period 1959:01-1999:04. The BEA news release on April 26th, 2000 also included the revised data for the 1946:01 - 1958:04 period. Our result held well also when the first period was included.

[12] See for example Campbell, Lo and MacKinlay (1997, page 269, Table 7.1), who use monthly data. These authors estimate the predictability regression in three different sample periods, 1927-1994, 1927-1951, and 1952-1994. As already mentioned, data for macroeconomic time series is available only from 1946.

extremely well in predicting future returns. Our results using quarterly data are comparable to the ones reported in Campbell et al. (1997) who instead used monthly data. For instance, for the one year and four year horizons they obtain R^2's of 18.8% and 41.7% respectively, matching our results almost to the point. The use of quarterly data then does not seem to be producing any particular bias in the results.

As can be seen in the first line of Table III, the ratio of labor income to consumption is now only a significant predictor at horizons of two years or more. The R^2 is 3% for the one year regression but rises to 22.6% for the four year regression. Interestingly, however, when both the dividend price ratio and the wages-to-consumption ratio are included – either in linear fashion as in regression (25) or in a nonlinear one as in regression (26) – the performance of the predictability regression improves considerably, with R^2 ranging between 25.1% for the one year regression to above 62.7% for the four year regression.

We can compare the results in Table III with those in Table IV, where the same exercise is carried out for the sample period 1952:01-1999:04. We include these results to show the dramatic decrease in the predictive power of the dividend price ratio due to the impressive stock market surge of the 90's (see e.g. Cochrane (1997) for a similar point) and to show how the labor income-to-consumption ratio still works well. Indeed, we see that over this sample period the dividend price ratio is never significant at any horizon and the R^2 of the predictive regressions does not go above 7% at any horizon. Instead, the wages-to-consumption ratio is performing quite well: The coefficients are statistically significant at all horizons and its predictive power ranges between 7.4% at the one year horizon to 35.4% at the four year horizon. As before, using both ratios greatly improves upon the predictability regression: using regression (25) for example we obtain R^2 ranging from 19.6% at the one year to above 56% at the four year horizon.

How does our model perform when confronted with the extraordinary stock market of the 90s? Figures 2 and 3 plot the time series of wages-to-consumption ratio, dividend price ratio and the four year cumulative stock return. As it can be seen in Figure 2, the dividend-price ratio and the cumulative four year return started moving in opposite directions at the end of the 80's. As already mentioned this is at the heart of the failure of the standard predictability regression (equation (24)) in our sample. However Figure 3 shows that the negative relation between the cumulative four year return and the ratio of labor income to consumption held well even in the last part of the sample. Still, our model cannot reconcile the very low dividend price ratios observed in the 90s with the high expected returns during the same period because low s_t^w imply relatively high dividend price ratios rather than low ones.

This is not unique to the model proposed in this paper. Barring bubbles, the low dividend price ratios and high expected returns observed in the 90s can only be rationalized with expectations of very high dividend growth or an impressive string of unexpected positive shocks to returns. Notice though that in the context of the model presented in section II there is still no room to simultaneously obtain low shares of labor income to consumption with low dividend price ratios. This though is an unfortunate feature of the log utility case and it can be proved that under more general preference specifications the dividend price ratio of the market portfolio depends on the entire distribution of dividend payments across the market.

The negative relation between the share of labor income to consumption and future stock returns has received subsequent support in a recent research by Lettau and Ludvigson (2001c). They isolate the permanent and transitory shocks of the cointegrated vector formed by consumption, labor earnings, and financial wealth. There are two permanent shocks of which only the "first" affects consumption. The second one they term income neutral as it does not result in any significant impact on consumption but rather "causes labor income to increase and asset wealth to decrease." A positive income neutral shock then results in an increase in the ratio of labor income to consumption which is followed by low financial returns as postulated in this paper.[13]

IV.B.2 Spurious regressions tests

Table I reports standard unit root tests. As can be seen, most series used in this paper are close-to-unit root series and hence there is a justified concern that the results about the time-series predictability may be due to spurious regressions.[14] In this section we tackle this problem by performing tests of spurious regressions as presented by Richardson and Stock (1989) and Torous and Yan (1999). We describe the procedure in detail in Appendix II, but, roughly, the test amounts to generate, by means of Monte Carlo simulations, the empirical distribution of the estimated regression coefficient under the null hypothesis that the population coefficient is zero. Such a distribution is reported in Table IX and we compare

[13]See Lettau and Ludvigson (2001c) pages 24-25 and their Figure 2.

[14]Aside from the original article by Phillips (1986), the reader is referred to Chap. 18.3 in Hamilton (1994) for a lucid exposition of the spurious regression problem and for other references.

the estimated coefficient in Tables II-IV to the cutoff points for the preferred confidence level.

For the sample period 1946-1999 the estimated coefficients reported in Table II-A are extremely close to being statistically significant at the 10% level for the one quarter, one year, and two year regression. For example, the one quarter ahead predictive regression yields a coefficient $\beta(1) = -.308$ while from the simulations, the 90% confidence interval is $[-0.309, 0.282]$. For the three and four year regression both coefficients are statistically significant at the 10% level. For instance for the four year regression the estimated coefficient is given by $\beta(16) = -4.902$ while the 90% confidence interval is $[-4.441, 4.129]$.

In contrast the dividend price ratio is never significant at the 10%. This is partly due to the fact that the correlation between returns and dividend price ratio, ρ, is much higher in this case (around $-.96$) than in the case where the predictive variable is the labor income to consumption ratio (in which case $\rho \approx -.02$). As explained in the appendix, a higher correlation ρ makes the distribution of $\beta(K)$ even more "non-normal". For example, using the dividend price ratio for the one quarter and four year regression we obtain $\beta(1) = .022$ and $\beta(K) = .475$ respectively while robust confidence intervals are $[-0.0027, 0.0598]$ and $[-0.048, 0.7655]$ respectively.

Looking at the regression where both the share and the log dividend price ratio enter linearly the estimated coefficient on s_w is significant at all horizons. For instance, for the one quarter predictability regression the estimated value of the coefficient is $\beta(1) = -.467$, whereas the 90% confidence interval is given by $[-.424, .363]$. Once again, the dividend price ratio is never significant at this level of statistical significance.

The results are even stronger when the sample is restricted to the period 1948-1999 (see Table II-B). The estimated coefficients for the univariate regression with s_w are all significant at the 10% level with the exception of the one year ahead regression, which is, in any case, extremely close to the cut-off value. All of them are statistically significant in the regression where the dividend price ratio enters linearly.

Overall, this section confirms from a statistical point of view that the predictive regression results obtained in the previous subsection section are unlikely to be spurious, and it lends further credence to the hypothesis of an economic relation linking returns on the aggregate market portfolio and the share of labor income to consumption.

IV.C Cross sectional Regressions

In this section we test the implications of the model for the cross-section of stock returns, which was developed in section III.C. Recall that the model has predictions for both the conditional CAPM and the conditional Consumption CAPM. We derive first specific testable implications and then conduct the empirical analysis on two sets of tests portfolios.

IV.C.1 Cross-sectional Implications

The starting point of our tests of the conditional CAPM is the beta representation given in expression (21). This conditional beta representation implies that both $\beta_{iw}(\mathbf{s}_t)$ and $\beta_{iM}(\mathbf{s}_t)$ are (complicated) functions of all the state variables, namely $(s_1, .., s_n)$. We argue though that the share of labor income to consumption is the most important common component driving the variation in "betas" and the conditional expected rates of return as it is, by far, the largest share. Furthermore, and as shown in equation (17), the beta of the total wealth portfolio is "almost" linear in s_t^w. By analogy with this we approximate the $\beta_{iw}(\mathbf{s}_t)$ and $\beta_{iM}(\mathbf{s}_t)$ in the two beta representation by:

$$\beta_{iw}(\mathbf{s}_t) \approx \beta_{iw1} + \beta_{iw2} s_t^w \quad \text{and} \quad \beta_{iM}(\mathbf{s}_t) \approx \beta_{iM1} + \beta_{iM2} s_t^w.$$

In this case (21) becomes

$$\begin{aligned} E_t[dR_i] &= \beta_{iw1} E_t[dR_t^w] + \beta_{iw2} E_t[s_t^w dR_t^w] \\ &\quad + \beta_{iM1} E_t\left[dR_t^M\right] + \beta_{iM1} E_t\left[s_t^w dR_t^M\right] \end{aligned}$$

We can condition down this expression to obtain

$$\begin{aligned} E\left[dR_t^i\right] &= \beta_{iw1} E[dR_t^w] + \beta_{iw2} E[s_t^w dR_t^w] \\ &+ \beta_{iM1} E\left[dR_t^M\right] + \beta_{iM2} E\left[s_t^w dR_t^M\right], \end{aligned} \tag{27}$$

which is the version of the conditional CAPM that we test below. Notice that the coefficients β_{ijk} for $j = w, M$ and $k = 1, 2$ are no longer regression coefficients as in a standard Conditional CAPM formulation. However, for the purpose of this paper we can test the predictions of our model by checking the improvement in the fit of the cross-sectional regression when we impose $\beta_{ij2} \neq 0$ for $j = w, M$. Indeed, by using a standard Fama-MacBeth (1972) procedure, the restricted case would imply a model with a "beta" that is independent of s_t^w, while the latter allows for a stochastic beta relationship.

Similarly the starting expression for our tests of the conditional Consumption CAPM is (22), and, as before if we assume, $\beta_i^c(\mathbf{s}_t) \approx \beta_{i1}^c + \beta_{i2}^c s_t^w$, we obtain

$$E_t\left[dR_t^i\right] = \beta_{i11}^c + \beta_{i12}^c s_t^w + \beta_{i21}^c E_t\left[\frac{dC_t}{C_t}\right] + \beta_{i22}^c E_t\left[s_t^w \frac{dC_t}{C_t}\right] \tag{28}$$

By taking the unconditional expectation in (28)

$$E\left[dR_t^i\right] = \beta_{i11}^c + \beta_{i12}^c E\left[s_t^w\right] + \beta_{i21}^c E\left[\frac{dC_t}{C_t}\right] + \beta_{i22}^c E\left[s_t^w \frac{dC_t}{C_t}\right] \tag{29}$$

and it is this last expression that we test in the empirical section.

IV.C.2 Empirical Results

In this section we test equations (27) and (29) in the set of test portfolios introduced by Fama and French (1993). In what follows we compare different specifications by reporting R^2, both adjusted and unadjusted, in the different regressions, but the reader should bear in mind that we have only 25 (cross-sectional) observations, the Fama-French portfolios, and that, as a consequence this statistic should be interpreted with caution.

a. Tests of the CAPM

Tests of equation (27) require an estimate of the return to human capital, which is not observable. We follow Jagannathan and Wang (1996) and LLa and proxy the return on human capital as the growth rate of wages $\Delta \log(w_t)$.[15]

Table V presents the main results of this section. There we test several empirical specifications that are consistent with the theoretical implications developed above. For every specification we report the estimate, the t-statisitic, and the Shanken (1992) corrected $t-$statisitic (in brackets). The last column reports the R^2 and, below it, the adjusted R^2 (in brackets). Our discussion centers around the adjusted R^2.

Panel A reports the results for our test of the conditional CAPM as given by expression (27). The first line shows the weak performance of the unconditional CAPM. The beta on the value weighted return is not statistically significant, enters with the wrong sign, and the R^2 is a just 10%, that is, the unconditional CAPM only explains 10% of the cross section of stock returns. The second line shows that adding the excess return on labor income R^w does not help much, given that the adjusted R^2 drops to 6%. A better definition of the market portfolio does not seem to improve the dismal performance of the CAPM.

Next we include the interaction term $s^w R^M$, that is, we assume that β_{iM2} in (27) is different from zero. Because s^w is slow moving, the joint presence of $s^w R^M$ and R^M can

[15]Our model yields a precise method to compute those returns by applying the pricing formula (11) to labor income. However, we found a correlation of about 90% between the two measures and the results were similar. For consistency with these other studies, we use the growth rate of wages as measure of return to labor.

result in severe multicollinearity problems. For this reason we include only the component of $s^w R^M$ that is orthogonal to R^M. As shown in line 3, conditioning market returns by the variable s^w dramatically improves the cross-sectional fit to an adjusted R^2 of 43%. The coefficient is strongly significant and positive. This sign is not easily interpretable as, recall, this only reflects the premium associated with the orthogonal component. As we shall see, the strong significance and explanatory power of the this term will be robust to different specifications and sample periods, lending credence to the mechanism emphasized in this paper. Surprisingly, the coefficient on R^M is now significant, but this is not stable across specifications. We share with many other studies[16] the negative sign in the market premium.

Adding labor income further improves the fit to an adjusted R^2 of 47% though the coefficient is not significant and enters with the wrong sign (see line 4.) Line 5 drops $s^w R^M$ in order to purely measure the impact of labor income, and it's scaled counterpart, on the cross section of stock returns.[17] The scaled factor is strongly significant and negative. As in the case of $s^w R^M$, this result is fairly stable throughout. Interestingly, the fit is fairly high, and the adjusted R^2 is 32%. Finally line 6 is the full specification as presented in equation (27). All coefficients are strongly significant, with the exception of the coefficient on R^w, and the adjusted R^2 achieves a robust 49%. The top two panels of Figure 4 offers a quick visual impression of the ability of the share of labor income to consumption to properly rearrange the set of tests portfolios.

In summary, the introduction of the share of labor income to consumption as a scaling variable considerably improves the performance of the CAPM. As already mentioned, we emphasize that our conditioning variable is not a financial variable and it is free of the concerns voiced by Berk (1995). He expressed that because returns are mechanically related to prices, ratios that have prices either in the numerator or denominator are in turn automatically related to returns, independently of whether they proxy for economically meaningful forces or not.

Table V also includes $t-$statistics using the correction in the computations of the standard errors proposed by Shanken (1992). This correction takes into account the fact that the betas are estimated rather than fixed.[18] In particular Shanken (1992) showed that under the

[16] See for instance Jagannathan and Wang (1996) and LLb

[17] As emphasized above in order to avoid multicollinearity problems we include only the component of $s^w R^w$ that is orthogonal to R^w. We follow this practice throughout.

[18] For a review of this point see Cochrane (2001), page 239.

assumption that asset returns have a conditional joint distribution with constant covariance matrix, the Fama-MacBeth procedure overstates the precision of the estimated parameters. As LLb note, the size of the correction is much larger when using macroeconomic factors than when using purely financial variables. Indeed, notice that for the standard CAPM there is essentially no difference between the uncorrected and the corrected $t-$statistic associated with R^M, whereas there is a much stronger correction when the share of labor income to consumption enters into the different specifications.[19]

Panel B of Table V reports similar regression results for the case where also s^w is entered in the cross-sectional regression as an independent factor. Although our test, as shown in equation (27), does not imply this regression, the results are nonetheless interesting to understand the effect of the labor-to-consumption ratio on the cross-section of stock returns. The first line in Panel B reports the CAPM regression where only s^w is added as explanatory variable and we see that the adjusted R^2 jumps to 45% (against 10% for the unconditional CAPM). Adding the scaled return on the market portfolio $s^w R^M$ increases the adjusted R^2 to 52% while when also the scaled return to labor is included the adjusted R^2 increases to 61%.

b. Robustness and comparison with related work

Our use of the sample period 1946-1998 is novel and the reader may have some concerns as to whether the results are robust to the more standard period 1963-1998, which was the one used originally by Fama and French (1993) and more recently by LLb. We show next that the results do indeed improve for this truncated sample.

Table VI reports the results for the sample period 1963-1998. First notice that the adjusted R^2 for the standard CAPM has collapsed to a dismal -2% as compared to 10% in the full sample. The very poor performance of the unconditional CAPM in this sample period and tests portfolios is indeed consistent with previous findings.[20]

As in the previous sample, the addition of the scaled market portfolio results in a remarkable improvement in the ability of the CAPM to explain the cross section. The coefficient is strongly significant and the adjusted R^2 is 46%. Again the role of $s^w R^M$ is robust through-

[19]However the Shanken (1992) corrected $t-$statistics should be interpreted with caution. As Jagannathan and Wang (1998) show, "the standard errors obtained from the Fama-MacBeth procedure need not necessarily overstate the precision of estimates," whenever the the assumption of conditional homoskedasticity is violated.

[20]For instance LLb, Table 1, line 1, report an adjusted R^2 of -3% for the unconditional CAPM.

out the various specifications. Adding labor income further improves the fit to 55% and the coefficient is now significant. Finally line 6 reports the full specification, which reports a slight improvement of the cross sectional fit over the sample period 1946-1998 (from 49% to 55%.) As before panel B shows the results where the variable s^w is included independently and again the results are very similar. Once gain, panels C and D of Figure 4 plot the unconditional and conditional performance of the CAPM in the 1963-1998 sample period.

A puzzling result of Table VI is that adding labor income growth as a proxy for the returns on human capital does not result in any improvement on the ability of the CAPM to explain the cross section of stock returns (see line 2.) This is all the more surprising in light of recent findings by LLb in the same set of test portfolios. These authors report an adjusted R^2 of 54% when they include labor income growth to improve on the definition of the market portfolio.[21] What is the reason behind this difference? The answer lies in the dating convention used in the construction of the labor income series.

Jagannathan and Wang (1996) use a dating convention that involves lagging the labor income series one month to account for the one month delay in the release of the data by the Bureau of Economic Analysis. The argument is that investors need information about the price of the human capital asset in order to form their optimal portfolios and that it is not reasonable to assume that they posses such information prior to it's release. LLb appeal to this argument to also use a lagged labor income series.

Unlike Jagannathan and Wang (1996), who use a monthly data set, we only have quarterly data. We lag the labor income by one quarter in order to provide agents with an information set comparable to that used by Jagannathan and Wang (1996). This time series has a correlation coefficient of .88 with the one used in LLb for their cross sectional study.[22]

Table VII contains the results where the labor income series has been lagged. In order to ease the comparison with LLb we report the results for the sample period 1963-1998. Clearly the only lines that are different with respect to Table VI are those that involve R^w. Notice that indeed now the return on human capital is a significant variable that greatly improves the performance of the CAPM. The adjusted R^2 goes from -2% in the case of the standard unconditional CAPM to 17% (see lines 1 and 2.) Furthermore, and as also found by LLb

[21] See their line 2 in Table 1. Jagannathan and Wang (1996) report a similar finding albeit in a different set of test portfolios and, most importantly, using monthly data.

[22] This dating convention in the case of quarterly data may be "too much." Still there is no alternative to this procedure when the data's frequency is quarterly.

and Jagannathan and Wang (1996), it enters with the right sign. A quick impression of this improvement can be obtained from panel C of Figure 5.[23]

Interestingly the main difference with respect to Table VI is that now scaling R^w with the share of labor income to consumption improves the performance of the CAPM to an adjusted R^2 of 54% as opposed to the 27% found with the unlagged labor income series (see line 5 in both Tables VI and VII.) Finally the full specification (line 6) is very similar to the previous one and the adjusted R^2 is 57% (see panels B and D of Figure 5.)

In summary, the role of s^w is then robust to different sample periods and alternative assumptions about the investors' information set. Furthermore most of the improvement comes from scaling returns, R^M and R^w, by the share of labor income to consumption, as prescribed by our model, a variable that is not automatically related to returns by construction.[24] Importantly it also has a significant explanatory power when it enters independently.

c. Tests of the CCAPM

Table VIII reports tests for the unconditional and conditional CCAPM as given by expression (29). As can be seen from panel A results for the period 1946-1998 are disappointing. The share of labor income to consumption does not seem to play any role in improving the appalling performance of the CCAPM. Only in the full specification is the share of labor income to consumption significant but the adjusted R^2 is just 2% (see panels A and B of Figure 6.)

The picture improves substantially in the sample period 1963-1998 (see panels C and D of Figure 6.) The inclusion of s^w results in significant coefficient and an adjusted R^2 of 15%. Scaling consumption growth does not seem to add any explanatory power to the CCAPM by itself. In contrast the full specification shown both s^w and $s^w \Delta c$ as significant regressors and the adjusted R^2 improves to a more respectable 30%.[25]

[23]Interestingly, in the sample 1946-1998 labor income does not improve the performance of the CAPM. See panel A of Figure 5.

[24]This robustness is important in light of recent work by Menzly (2001) who shows that tests of the conditional CAPM may suffer from a low power problem. In particular he shows that "most portfolios constructed using US postwar returns data have little ability in distinguishing between an economically meaningful scaling variable and a random variable with no economic content."

[25]As in the case of the CAPM we only include the orthogonal component, that is, the part of $s^w \Delta c$ that is orthogonal to s^w and Δc.

V. FURTHER TESTS AND CONCLUDING REMARKS

We propose a simple general equilibrium model to show that changes in expected returns may be generated by changes in the relative importance of various sources of income. In our model, total income is funded by dividends and labor income that grow stochastically over time. We show that equilibrium expected returns change as the fraction of total income funded by labor income fluctuates over time, because the latter affects the conditional covariance between equilibrium returns and consumption growth. We then obtain a new and simple testable implication, namely, that the ratio of labor income to consumption should help predicts stock returns. This is strongly confirmed in the data. The regression of stock returns on lagged values of this ratio produces statistically significant coefficients and adjusted R^2 that are larger than those generated when using the dividend price ratio as a single explanatory variable. Notice that differently from the dividend price ratio, our variable is a pure macroeconomic variable that is constructed with no reference to financial variables and it is in this sense that we provide a powerful test of our theory.

We derive and test a version of the conditional CAPM and the conditional consumption CAPM, where the variable we use to condition is the aforementioned ratio. Tests are conducted on the 25 Fama-French portfolios. We find that when we use our labor-income to consumption ratio as conditioning variable, the CAPM does a substantially better job in capturing cross sectional variation in returns. The result is robust to alternative sample periods and dating conventions regarding the returns on the human capital asset. Results for the Consumption CAPM are more disappointing.

In addition to the robustness tests performed above, a previous version of the paper contained others that further confirmed the share of labor income to consumption as an economically meaningful variable.

First we checked the robustness of our results to alternative specifications of the variable s^w. For instance the model proposed in this paper implies that total consumption equals total income in equilibrium. As a consequence, the same relationships that hold for the labor income to consumption ratio should also hold for the labor income to total income ratio.[26]

[26]For coherence with the labor income series (which is net of taxes), we took the total *disposable* income as a measure of total income. It is worth reminding the relationship between total income and disposable income in the national accounts (NIPA tables). We have Total Personal Income equals Compensation of Employees plus Proprietors Income plus Rental Income plus Personal Dividend Income plus Personal Interest

These regressions showed that the ratio of labor income to disposable income ratio has a very good predictive power for future returns in *all* subsamples, although the results were not so strong for the one quarter ahead predictive regression.

We also performed a direct test of our theory. Essentially the economic model that motivated our empirical investigation entails that the covariance between returns and consumption growth moves over time due to the change in the ratio between labor income and total consumption. In order to test whether the ratio between labor income and consumption predicts the level of covariance between returns and real consumption growth, we first obtained an estimated time series of the latter by fitting a bi-variate GARCH(1,1) model to data from 1946-1999. We then ran a regression of the estimated covariance versus past covariances and the share of labor income to consumption. Again the share of labor income to consumption obtained as a significant predictor of changes in the covariance between returns and consumption growth.[27]

We also tested the cross sectional implications of our model the alternative set of test portfolios used by Jagannathan and Wang (1996), which were portfolios sorted by size and beta.[28] In the full specification of our model the adjusted R^2 was 18% and rose to 55% when the share of labor income to consumption was independently included. Furthermore tests of the CCAPM in this set of tests portfolios resulted in adjusted R^2 as high as 38%. These results were also robust to alternative dating conventions concerning human capital returns.

In conclusion, we find a substantial support for the economic model proposed in this paper, that is, that the time variation in the relative importance of the various sources of income has an important effect on the required expected return. Furthermore, our model is also fully consistent with a recent body of of evidence uncovered by Martin Lettau and Sydney Ludvigson documenting that cyclical variation in the consumption to wealth ratio affect future expected returns. Although our model is presented in the log-utility case for simplicity, which implies a constant consumption to wealth ratio, the same results of this paper can be obtained with higher degrees of risk aversions, as shown in the appendix. In this case, one can show that the consumption to wealth ratio is a non-linear but decreasing function of the labor income to consumption ratio. Hence, this model predicts that the

Income plus Transfer payments to persons *less* Personal Contribution to Social Insurance. Finally, Disposable Income equals Total Income less Personal Taxes.

[27] Of course, and as emphasized in the introduction, our model cannot explain the *level* of this covariance.

[28] The sample period in these portfolios is 1963-1990.

consumption to wealth ratio should also be a predictor of future returns, a finding that is well documented in LLa.

References

Barberis, Nick, Ming Huang and Tano Santos (2001), "Prospect Theory and Asset Prices," *Quarterly Journal of Economics,* February.

Berk, Jonathan B. (1995), "A critique of size-related anomalies," *Review of Financial Studies,* 8, 275-286.

Berk, Jonathan B., Richard C. Green, and Vasant Naik (1999), "Optimal Investment, Growth Options, and Security Returns," *Journal of Finance,* vol. LIV no. 5, 1553-1607.

Campbell, John Y. (1987), "Stock Returns and the Term Structure," *Journal of Financial Economics,* 18, 373-399.

Campbell, John Y. (1996), "Understanding Risk and Return," *Journal of Political Economy*, 104, 298-345.

Campbell, John Y. (1999), "Asset Prices, Consumption, and the Business Cycle," in Handbook of Macroeconomics, John B. Taylor and Michael Woodford editors.

Campbell, John Y. (2000), "Asset Pricing at the Millennium." *Forthcoming Journal of Finance*, August.

Campbell, John Y. and John H. Cochrane (1999), "By Force of Habit," *Journal of Political Economy.*

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay (1997), The Econometrics of Financial Markets. Princeton University Press, Princeton, New Jersey.

Campbell, John Y. and Robert J. Shiller (1988 a), "The Dividend Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies,* 1, 195-227.

Campbell, John Y. and Robert J. Shiller (1988 b), "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance*, 43, 661-676.

Cochrane, John H. (1996), "A Cross Sectional Test of an Investment Based Asset Pricing Model," *Journal of Political Economy,* 104 (3), 572-621.

Cochrane, John H. (1997), "Where is the Market Going? Uncertain Facts and Novel Theories," *Economic Perspectives*, Federal Reserve of Chicago, November-December..

Cochrane, John H. (2000), "New Facts in Finance," *Economic Perspectives. Federal Reserve Bank of Chicago.*

Cochrane, John H. (2000), Asset Pricing, Princeton University Press, Princeton, NJ.

Fama, Eugene F. and James D. MacBeth (1972), "Risk, Return, and Equilibrium: Empirical Tests," Journal of Political Economy, 81, 607-636.

Fama, Eugene F. and G. William Schwert (1977), "Human Capital and Capital Market Equilibrium," *Journal of Financial Economics,* 4, 115-146.

Fama, Eugene F. and Kenneth R. French (1988 a), "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics,* 22, 3-27.

Fama, Eugene F. and Kenneth R. French (1988 b), "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy,* 96, 246-273.

Fama, Eugene F. and Kenneth R. French (1989), "Business Conditions and Expected Returns on Stocks and Bonds," *Journal of Financial Economics,* 25, 23-49.

Fama, Eugene F. and Kenneth R. French (1992), "The Cross Section of Expected Returns," *Journal of Finance,* 47, 427-465.

Fama, Eugene F. and Kenneth R. French (1993), "Common Risk Factors in the Returns of Stocks and Bonds," *Journal of Financial Economics,* 33, 3-56.

Ferson, Wayne E. and Campbell R. Harvey (1999), "Conditioning Variables and the Cross Section of Stock Returns," *Journal of Finance*, 54, 1325-1361.

Jagannathan, R. and Zhenyu Wang (1996), "The Conditional CAPM and the Cross Section of Expected Returns," *Journal of Finance,* 51, 3-54.

Jagannathan, R. and Zhenyu Wang (1998), "An Asymptotic Theory for Estimating Beta-Pricing Models Using Cross-Sectional Regression," *Journal of Finance,* 53 no. 4, 1285-1309.

Hamilton, James D. (1994), Time Series Analysis, Princeton University Press, Princeton, New Jersey.

Hodrick, Robert (1992), "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement," *Review of Financial Studies,* 5, 357-386.

Keim, Donald B. and Robert F. Stambaugh (1986), "Predicting Stock Returns in the Stock and Bond Markets," *Journal of Financial Economics,* 17, 357-390.

Gomes, Joao, Leonid Kogan, and Lu Zhang (2001), "Equilibrium Cross Section of Returns," working paper, Wharton School.

Lamont, Owen (1998), "Earnings and Expected Returns," *Journal of Finance*, 53, 1563-1587.

Lettau, Martin and Sydney Ludvigson (2001a), "Consumption, Aggregate Wealth and Expected Stock Returns," forthcoming *Journal of Finance.*

Lettau, Martin and Sydney Ludvigson (2001b), "Resurrecting the (C)CAPM: A Cross-Sectional Test of Linear Factor Models When Risk Premia are Time-Varying," forthcoming *Journal of Political Economy.*

Lettau, Martin and Sydney Ludvigson (2001c), "Understanding Trend and Cycle in Asset Values," working paper, Federal Reserve of New York.

Lucas, Robert E. (1978), "Asset Prices in an Exchange Economy," *Econometrica* 46, 1429-1445.

Mayers, David, (1972) "Nonmarketable Assets and Capital Market Equilibrium under Uncertainty," in M. Jensen ed.: *Studies in the Theory of Capital Markets.* Praeger, New York, 223-248.

Menzly, Lior, (2001) "Cross-Sectional Tests of the Conditional C-CAPM," working paper, Graduate School of Business, University of Chicago.

Phillips, Peter C. B. (1986), "Understanding Spurious Regressions in Econometrics," *Journal of Econometrics,* 33, 311-340.

Richadson, Matthew and James Stock (1989), "Drawing inferences from statistics based on multiyear asset returns," *Journal of Financial Economics,* 25, 323-348.

Shanken, Jay (1992), "On the estimation of beta-pricing models," it Review of Financial Studies, 5, 1-33.

Shiller, Robert J. (1981), "Do prices move too much to be explained by subsequent changes in dividends?," *American Economic Review,* 71, 421-436.

Timmerman, Allan (1993), "How Learning in Financial Markets Generates Excess Volatility and Predictability in Stock Prices," *Quarterly Journal of Economics*, 108, 1135-1145.

Timmerman, Allan (1996), "Excess Volatility and Predictability of Stock Returns in Autoregressive Dividend Models with Learning," *Review of Economic Studies*, 1996, 523-557.

Torous, Walter and Shu Yan (1999), "Predictive Regressions Revisited," working paper, UCLA.

Veronesi, Pietro (2000), "How Does Information Quality Affect Stock Returns?" *Journal of Finance*, 55, 807-837.

Appendix

I. Proofs and extensions

In this appendix we generalize some of the results obtained in the body of the paper. We start with a more general model for the vector process for shares $\mathbf{s}_t = \left(s_t^1, ..., s_t^n\right)$. Let $\mathbf{s}_t$ be a $1 \times n$ vector evolving according to the stochastic differential equations

$$ds_t^i = [\mathbf{s}_t \mathbf{\Lambda}]_i \, dt + s_t^i \sigma_i\left(\mathbf{s}_t\right) d\mathbf{B}_t \tag{30}$$

where $\mathbf{s}_0 = \widehat{\mathbf{s}}$ with $\sum_{i=1}^n \widehat{s}^i = 1$, $\mathbf{\Lambda}$ is a matrix with the property that $\lambda_{ij} \geq 0$ for all ij and $\lambda_{ii} = -\sum_{j \neq i} \lambda_{ij}$ and finally

$$\sigma_i\left(\mathbf{s}_t\right) = \left(\nu_i - \sum_{j=1}^n s_t^j \nu_j\right)$$

and where ν_i and $1 \times n$ vectors. In other words, (30) is the continuous time analog of a standard multivariate autoregressive process for the fractions s_i, with some restrictions on $\mathbf{\Lambda}$ and $\sigma_i(s)$ to make sure that $\sum_{i=1}^n s_i(t) = 1$ for all t. Notice that by choosing the parametrization of the matrix $\mathbf{\Lambda}$ as $\lambda_{ij} = a\overline{s}^i$ for $i \neq j$, where $\sum_{j=1}^n \overline{s}^j = 1$ (which implies $\lambda_{ii} = a\overline{s}_i - a$) yields the case studied in the body of the paper, namely

$$ds_i = a\left(\overline{s}_i - s_i\right) dt + s_i \sigma_i\left(\mathbf{s}_t\right) d\mathbf{B}_t \tag{31}$$

We next assume that

$$U(C,t) = \begin{cases} e^{-\phi t} \frac{C^{1-\gamma}}{1-\gamma} & \text{for} \quad \gamma \neq 1 \\ e^{-\phi t} \log(C) & \text{for} \quad \gamma = 1 \end{cases}$$

We now prove the following:

Proposition A1 *Let either of the following assumptions hold:*

I. *Investors have log-utility:* $U(t, C) = e^{-\phi t} \log(C)$.

II. *Investors have power utility* ($\gamma \neq 1$) *but consumption growth is* $\mu_{c,t} = \overline{\mu}_c + \sum_{i=1}^n s_t^i \theta_i$, *where* $\overline{\mu}_c$ *is constant and* $\theta_i = \nu_i \sigma_c'$.

Then the stock market price is

$$P_t^i = \sum_{j=1}^n B_{ij} D_t^j$$

where $D_t^1 = w_t$ and the coefficients B_{ij} are the ij elements of the matrix $\mathbf{B}$ given by

$$\mathbf{B} = \left(\phi \mathbf{I} - \Lambda'\right)^{-1}$$

in case (a); and

$$\mathbf{B} = \left(\widehat{\Theta} - \Lambda'\right)^{-1}$$

with $\widehat{\Theta} = diag\left(\widehat{\theta}_1, ..., \widehat{\theta}_n\right)$ with $\widehat{\theta}_i = \phi + (\gamma - 1)(\overline{\mu}_c + \theta_i) - \frac{1}{2}\gamma(\gamma - 1)\sigma_c^2$ in case (b), respectively.

We first prove the following Lemma. For notational convenience, let $\beta = 1 - \gamma$.

Lemma A1: *For all $i = 1, .., n$, let $\mu_{c,t} = \overline{\mu}_c + \sum_{j=1}^n s_t^j \theta_j$, $\widehat{\theta}_i = \phi - \beta(\overline{\mu}_c + \theta_i) - \frac{1}{2}\beta(\beta - 1)\sigma_c^2$ and $\widehat{\Theta} = diag\left(\widehat{\theta}_1, ..., \widehat{\theta}_n\right)$. Then*

$$E_t\left[C_u^\beta s_u^i\right] = \sum_{k=1}^n C_t^\beta s_t^k \sum_{j=1}^n w_{jk}^{-1} w_{ij} e^{\omega_j(u-t)}$$

where ω_j are the eigenvalues of $\overline{\Lambda}' = \left(\Lambda' + \phi\mathbf{I} - \widehat{\Theta}\right)$ and w_{ij} are associated eigenvectors and $w_{ij}^{-1} = [W^{-1}]_{ij}$.

Proof of Lemma A1: Let

$$X_t^i = C_t^\beta s_t^i \tag{32}$$

Apply Ito's lemma to find

$$\begin{aligned}
dX_t^i &= \beta C_t^{\beta-1} s_t^i dC_t + \frac{1}{2}\beta(\beta - 1)C_t^{\beta-2} s_t^i dC_t^2 && (33)\\
&\quad + C_t^\beta ds_t^i + \beta C_t^{\beta-1} ds_t^i dC_t && (34)\\
&= \beta C_t^{\beta-1} s_t^i C_t \mu_{c,t} dt + \beta C_t^{\beta-1} s_t^i C_t \sigma_c d\mathbf{B}_t && (35)\\
&\quad + \frac{1}{2}\beta(\beta - 1) C_t^{\beta-2} s_t^i C_t^2 \sigma_c^2 dt && (36)\\
&\quad + C_t^\beta [\mathbf{s}_t \mathbf{\Lambda}]_i dt + C_t^\beta s_t^i \sigma_i(\mathbf{s}_t) d\mathbf{B}_t + \beta C_t^{\beta-1} s_t^i \sigma_i(\mathbf{s}_t)\sigma_c' C_t && (37)\\
&= \left\{\beta X_t^i \mu_{c,t} + \frac{1}{2}\beta(\beta - 1) X_t^i \sigma_c^2 + [\mathbf{X}_t \mathbf{\Lambda}]_i + \beta \mathbf{X}_t^i \sigma_i(\mathbf{s}_t)\sigma_c'\right\} dt && (38)\\
&\quad + X_t^i \{\beta\sigma_c + \sigma_i(\mathbf{s}_t)\} d\mathbf{B}_t && (39)
\end{aligned}$$

This stochastic differential equation is non-linear in the drift, due to the covariance term $\beta X_t^i \sigma_i(\mathbf{s}_t)\sigma_c' = \beta X_t^i \left(\theta_i - \sum_{j=1}^n s_t^j \theta_j\right)$. However, in both cases (a) and (b) we find that it actually becomes linear: In case (a) we have $\beta = 0$ (which also implies that $X_t^i = s_t^i$) while in case (b) we assumed

$\mu_c = \overline{\mu}_c + \sum_{j=1}^{n} s_j\theta_j$, which cancels with the non-linear part of the drift. In either case (by setting $\beta = 0$ in case (a), we then obtain

$$\begin{aligned} dX_t^i &= \left\{\beta X_t^i \overline{\mu}_c + \frac{1}{2}\beta(\beta-1) X_t^i \sigma_c^2 + [\mathbf{X}_t \mathbf{\Lambda}]_i + \beta X_t^i \theta_i\right\} dt \\ &\quad + X_t^i \{\beta\sigma_c + \sigma_i(\mathbf{s}_t)\} d\mathbf{B}_t \\ &= \left[\mathbf{X}_t\left(\mathbf{\Lambda} + \phi\mathbf{I} - \widehat{\Theta}\right)\right]_i dt + X_t^i\{\beta\sigma_c + \sigma_i(\mathbf{s}_t)\} d\mathbf{B}_t \end{aligned}$$

Defining $\overline{\mathbf{\Lambda}} = \left(\mathbf{\Lambda} + \phi\mathbf{I} - \widehat{\Theta}\right)$ and $\widehat{\sigma}_i(\mathbf{s}_t) = \beta\sigma_c + \sigma_i(s)$ we can rewrite

$$dX_t^i = \left[\mathbf{X}_t\overline{\mathbf{\Lambda}}\right]_i dt + X_t^i \widehat{\sigma}_i(\mathbf{s}_t) d\mathbf{B}_t$$

Using the vector notation, with $\mathbf{X} = \left(X^1, ..., X^n\right)$ as a $1 \times n$ vector, we can rewrite this in its integral form as

$$\mathbf{X}_u = \mathbf{X}_t + \int_t^u \mathbf{X}_\tau \overline{\mathbf{\Lambda}} d\tau + \int_t^u X_\tau \widehat{\mathbf{\Sigma}}(\mathbf{s}_\tau) d\mathbf{B}_\tau \tag{40}$$

Notice that also that for all i, $X_t^i < C_t^i$. Hence, all the integral below exist as long as the expected present value of future consumption can be computed, which in turn is ensured by choosing ϕ sufficiently large. Let $\widetilde{\mathbf{X}}_u = E_t(\mathbf{X}_u)$. Since $\widehat{\Sigma}(s)$ is bounded,

$$E_t\left[\int_t^u \mathbf{X}_\tau \widehat{\mathbf{\Sigma}}(\mathbf{s}_\tau) d\mathbf{B}_u\right] = 0$$

Hence, taking expectations on both sides of (40) with respect to time t we obtain

$$\widetilde{\mathbf{X}}_u = \mathbf{X}_t + \int_t^u \widetilde{\mathbf{X}}_\tau \overline{\mathbf{\Lambda}} d\tau$$

or

$$\frac{d\widetilde{\mathbf{X}}}{d\tau} = \widetilde{\mathbf{X}}\overline{\mathbf{\Lambda}}$$

This is a linear system of differential equations with initial condition $\widetilde{\mathbf{X}}_0 = \mathbf{X}_t$. If $\overline{\Lambda}'$ admits real and distinct eigenvalues, its general solution is then given by

$$\widetilde{X}_u^i = \sum_{j=1}^{n} k_j w_{ij} e^{\omega_j(u-t)}$$

where ω_j are the eigenvalues of $\overline{\Lambda}'$ and w_{ij} are associated eigenvectors. From the initial condition $\widetilde{\mathbf{X}}_0 = X_t$ we obtain that $\mathbf{X}_t = \mathbf{W} \times \kappa$ where $\mathbf{W} = [w_1, .., w_n]$ is the matrix whose columns are the eigenvectors of $\overline{\Lambda}'$. Hence, $\kappa = \mathbf{W}^{-1} \times \mathbf{X}_t$ or

$$\kappa_j = \sum_k w_{jk}^{-1} X_t^k$$

which implies

$$\widetilde{X}_u^i = \sum_{j=1}^n \sum_{k=1}^n w_{jk}^{-1} X_t^k w_{ij} e^{\omega_j(u-t)} = \sum_{k=1}^n X_t^k \sum_{j=1}^n w_{jk}^{-1} w_{ij} e^{\omega_j(u-t)}$$

where $w_{ij}^{-1} = [W^{-1}]_{ij}$. This concludes the proof of Lemma A1.■

Proof of Proposition A1: Consider the usual pricing equation

$$\begin{aligned} P_t^i &= E_t\left[\int_t^\infty \frac{U_C(C_u,u)}{U_C(C_t,t)} D_u^i du\right] = E_t\left[\int_t^\infty e^{-\phi(u-t)}\left(\frac{C_u}{C_t}\right)^{-\gamma}\left(s_u^i C_u\right) du\right] \\ &= C_t^\gamma E_t\left[\int_t^\infty e^{-\phi(u-t)} C_u^{1-\gamma} s_u^i du\right] \end{aligned}$$

We can prove both (a) and (b) at the same time by making use of Lemma A1. The only difference is on γ. From (32) by setting $\beta = 1-\gamma$ we have

$$\begin{aligned} P_t^i &= C_t^\gamma E_t\left[\int_t^\infty e^{-\phi(u-t)} C_u^{1-\gamma} s_u^i du\right] = C_t^\gamma E_t\left[\int_t^\infty e^{-\phi(u-t)} X_u^i du\right] && (41) \\ &= C_t^\gamma \sum_{k=1}^n X_t^k \sum_{j=1}^n w_{jk}^{-1} w_{ij} \int_t^\infty e^{-(\phi-\omega_j)(u-t)} du && (42) \\ &= C_t^\gamma \sum_{k=1}^n C_t^{1-\gamma} s_t^k \sum_{j=1}^n w_{jk}^{-1} w_{ij} \int_t^\infty e^{-(\phi-\omega_j)(u-t)} du && (43) \\ &= C_t \sum_{k=1}^n s_t^k \left(\sum_{j=1}^n w_{jk}^{-1} w_{ij} \frac{1}{\phi-\omega_j}\right) = \sum_{k=1}^n C_t s_t^k \left(\sum_{j=1}^n w_{jk}^{-1} w_{ij} \frac{1}{\phi-\omega_j}\right) && (44) \\ &= \sum_{k=1}^n D_t^k \left(\sum_{j=i}^n w_{jk}^{-1} w_{ij} \frac{1}{\phi-\omega_j}\right) && (45) \\ &= \sum_{k=1}^n D_t^k B_{ik} && (46) \end{aligned}$$

where

$$B_{ik} = \sum_{j=i}^n w_{jk}^{-1} w_{ij} \frac{1}{\phi-\omega_j}$$

We finally prove that

$$\left(\sum_{j=1}^n w_{jk}^{-1} w_{2j} \frac{1}{\phi-\omega_j}\right) = B_{ik} = e_i\left(\widehat{\Theta}-\Lambda'\right)^{-1} e_k = e_i\left(\phi\mathbf{I}-\overline{\Lambda}'\right)^{-1} e_k$$

By definition $\overline{\mathbf{\Lambda}} = \left(\mathbf{\Lambda} + \phi\mathbf{I} - \widehat{\Theta}\right)$ and hence $\overline{\Lambda}' = \left(\Lambda' + \phi\mathbf{I} - \widehat{\Theta}\right)$. Let Ω the diagonal matrix with the eigenvalues ω_j of $\overline{\Lambda}'$ on the principal diagonal. We then have:

$$\mathbf{B} = W\left(\mathbf{I}\phi - \Omega\right)^{-1} W^{-1} \tag{47}$$

In fact, by letting $D = \left(\mathbf{I}\phi - \Omega\right)^{-1}$ in this case the ik element of $\mathbf{B}$ can be written as

$$B_{ik} = \sum_j \sum_\ell w_{ij} D_{j\ell} w_{\ell k}^{-1} = \sum_{j=1}^{n} \frac{w_{ij} w_{jk}^{-1}}{\phi - \omega_j}$$

The identity $\mathbf{W}\left(\mathbf{I}\phi - \Omega\right)^{-1}\mathbf{W}^{-1} = \left(\phi I - \overline{\mathbf{\Lambda}}'\right)^{-1}$ yields the result. This concludes the proof. ■

Proposition A2. For the log-utility case with the share process evolving as

$$ds_t^i = a\left(\overline{s}^i - s_t^i\right)dt + \sigma\left(\mathbf{s}_t\right)d\mathbf{B}_t$$

we have that the cross-sectional expected returns are

$$E_t\left[dR_t^i\right] = \beta_i\left(\mathbf{s}_t\right)E_t\left[dR_t^{TW}\right]$$

with

$$\beta_i\left(\mathbf{s}_t\right) = 1 + \left(\frac{\theta_i}{\sigma_c\sigma_c'\left(1 + \frac{a}{\phi}\left(\frac{\overline{s}^i}{s_t^i}\right)\right)}\right)s_t^w + \left(\frac{1}{\sigma_c\sigma_c'\left(1 + \frac{a}{\phi}\left(\frac{\overline{s}^i}{s_t^i}\right)\right)}\right)\sum_{j\neq 1,i} s_t^j\left(\theta_i - \theta_j\right) \tag{48}$$

Proof: First, notice that from the pricing relation (11) the value of the total wealth portfolio is

$$P_t^{TW} = \sum_{i=1}^{n} P_t^i = C_t\left\{\frac{a\sum_{i=1}^{n}\overline{s}^i}{\phi\left(a+\phi\right)} + \frac{\sum_{i=1}^{n}s_t^i}{a+\phi}\right\} = \frac{1}{\phi}C_t \tag{49}$$

Hence, we have that the excess returns on the total wealth portfolio

$$dR_t^{TW} = \frac{dP_t^{TW} + \left(w_t + \sum_{i=2}^{n} D_t^i\right)dt}{P_t^{TW}} - r_t dt$$

evolves according to the process

$$dR_t^{TW} = \frac{dC_t}{C_t} + \left(\phi - r_t\right)dt = \mu_{R,TW}dt + \sigma_{R,TW}d\mathbf{B}_t \tag{50}$$

with

$$E_t\left[dR_{TW}\right] = \mu_c dt + \left(\phi - r_t\right)dt = \sigma_c\sigma_c' dt \text{ and } \sigma_{R,TW} = \sigma_c \tag{51}$$

From the Consumption CAPM equilibrium condition $E_t\left[dR_t^i\right] = cov_t\left(dR_t^i, \frac{dC_t}{C_t}\right)$ it follows that $E_t\left[dR_t^i\right] = cov_t\left(dR_t^i, dR_t^{TW}\right)$ which, by using (51) can be turned into

$$E_t\left[dR_t^i\right] = \frac{cov_t\left(dR_t^i, dR_t^{TW}\right)}{var_t\left(dR_t^{TW}\right)} E_t\left[dR_i^{TW}\right]$$

Finally, by Ito's lemma on the excess return

$$dR_t^i = \frac{dP_t^i + D_t^i dt}{P_t^i} - r_t dt$$

we find $dR_t^i = \mu_{R,t}^i dt + \sigma_R^i\left(\mathbf{s}_t\right) d\mathbf{B}_t$ with

$$\sigma_R^i\left(\mathbf{s}_t\right) = \sigma_c + \frac{\nu_i - \sum_{k=1}^n s_t^k \nu_k}{\left(1 + \frac{a\bar{s}^i}{\phi s_t^i}\right)}$$

Finally, by recalling again that $\sigma_{R,TW} = \sigma_c$ the "beta" can be computed directly as

$$\begin{aligned}
\beta_i\left(\mathbf{s}_t\right) &= \frac{cov_t\left(dR_t^i, dR_t^{TW}\right)}{var_t\left(dR_t^{TW}\right)} = \frac{\sigma_R^i\left(\mathbf{s}_t\right)' \sigma_{R,TW}}{\sigma_{R,TW}' \sigma_{R,TW}} \\
&= \frac{1}{\sigma_c \sigma_c'}\left(\sigma_c \sigma_c' + \frac{\theta_i - \sum_{k=1}^n s_t^k \theta_k}{\left(1 + \frac{a\bar{s}^i}{\phi s_t^i}\right)}\right) \\
&= 1 + \frac{\theta_i}{\sigma_c \sigma_c'\left(1 + \frac{a\bar{s}^i}{\phi s_t^i}\right)} s_t^w + \frac{1}{\sigma_c \sigma_c'\left(1 + \frac{a\bar{s}^i}{\phi s_t^i}\right)} \sum_{j \neq 1,i} s_t^j\left(\theta_i - \theta_j\right)
\end{aligned}$$

where we also used the fact that in (6) and (7) that

$$\theta_i - \sum_{j=1}^n s^j \theta_j = cov_t\left(\frac{ds_t^i}{s_t^i}, \frac{dC_t}{C_t}\right) = s_t^w \theta_i + \sum_{j \neq 1,i} s_t^j\left(\theta_i - \theta_j\right)$$

Appendix II. Spurious regression tests

We describe the particular spurious regression tests as presented in Torous and Yan (1999), who closely follow Richardson and Stock (1989). Suppose that we have the pair of series

$$y_{t+1} = a + b x_t + u_{t+1} \quad (52)$$

$$x_{t+1} = \alpha + \phi x_t + v_{t+1} \quad (53)$$

where $y_t = \log(R_t)$ is the log return and where $\varepsilon_t = (u_t, v_t)'$ is a martingale difference sequence such that $E[\varepsilon_t \varepsilon_t' | \varepsilon_{t-1}, \varepsilon_{t-2}...] = \Sigma$ and such that u_t and v_t have only contemporaneous correlation $\rho = Corr(u_t, v_t)$. Tourus and Yan (1999) study the asymptotic distribution of the least square estimator obtained by regressing the long-term return $y_{t+1}(K) = \sum_{i=1}^{K} y_{t+i}$ onto the predictive variable x_t under the null hypothesis that there is no relation between y_t and x_t but through the contemporaneous correlation of the series. That is, the null-hypothesis is $\mathcal{H}_0 : b = 0$. They show that indeed the for given K, the estimated $\beta(K)$ is consistent as $T \to \infty$, but its Newey-West adjusted t-statistic $t_{\beta(K)}$ has a non-standard distribution which depends on the correlation ρ between u_t and v_t. If $\rho = 0$, then $t_{\beta(K)}$ has indeed a standard normal distribution. They also show that if the number of non-overlapping intervals does not grow to infinity with T, that is if $T/K \to c$, constant, then $\beta(K)$ is no longer consistent and $t_{\beta(K)}$ has a non-standard distribution that depends on both ρ and c.

In order to check the robustness of our results, we take the suggestions contained in Torous and Yan (1999) and obtain more robust confidence intervals for the coefficient $\beta(K)$ in our predictive regressions by means of Monte Carlo Simulations. More specifically, we perform the following exercise: Let x_t in equation (53) be any of the regressors used in the forecasting regressions, i.e. the labor-income to consumption ratio $s_{w,t}$, the (log) dividend price ratio $\log(D_t/P_t)$, both of them or the interaction term $s_{w,t} \log(D_t/P_t)$. For each of them, we first compute the parameters α and ϕ in equation (53) from a time-series regression and the matrix $\Sigma = E[\varepsilon_t \varepsilon_t']$ to take into account the correlation between u_t and v_t (recall that if the correlation $\rho = 0$, then $\beta(K)$ is indeed consistent as $T \to \infty$ and $t_{\beta(K)}$ is indeed distributed as a standard normal distribution. In this case all the results in the previous section hold.) Given our sample size $T = 216$ for the period 1946-1999, we simulate 10,000 paths of the system (52)-(53) under the null hypothesis that $b = 0$. For each sample, we compute the predictive regressions as in equations (23)-(26) and obtain a distribution for $\beta(K)$. This is tabulated in Table VII. We repeated the experiment using both the estimations of the relevant parameters of (52)-(53) and the sample sizes corresponding to the periods 1952-1999 and 1952-1994 and obtained extremely similar cutoff values for $\beta(K)$, which we do not report for brevity.

TABLE I

Summary Statistics: 1946:01 - 1999:04

	mean (quarterly)	st.dev. (quarterly)	1st. Autcorrelation	β OLS	Dickey Fuller
Returns	0.0172	0.0798	0.0442	0.024	-
$\log(D/P)$	-3.36	0.34	0.9746	0.9987	$-.2819$
w/C	0.8307	0.0374	0.9753	0.9876	-2.674

Correlation Matrix

	Returns	$\log(D/P)$	w/C
Returns	1	-	-
$\log(D/P)$	-0.1271	1	-
w/C	-0.1338	0.4306	1

Notes for Table I: Summary statistics of time series data. The last two columns report the value of the regression coefficient of an OLS regression on own lagged variable. The Dickey-Fuller statistic is also reported. Rejection of unit-root hypothesis at 1%, 5% and 10% level is for statistics below -13.6, -8.0 and -5.7, respectively.

TABLE II A

Forecasting Future Returns

Sample: 1946:01 - 1999:04

	Forecasting Horizon				
K	1	4	8	12	16
w/C	-0.308	-1.121	-2.275	-3.588	-4.902
t-stat.	(-2.140)	(-2.407)	(-3.029)	(-3.721)	(-4.028)
(adj) R^2	0.016	0.061	0.143	0.250	0.346
$log(D/P)$	0.022	0.105	0.213	0.338	0.475
t-stat.	(1.394)	(1.648)	(1.445)	(1.590)	(1.840)
(adj) R^2	0.003	0.039	0.084	0.142	0.207
w/C	-0.467	-1.660	-2.995	-4.237	-5.315
t-stat.	(-2.955)	(-2.960)	(-3.525)	(-4.371)	(-4.733)
$log(D/P)$	0.043	0.173	0.312	0.435	0.538
t-stat.	(2.800)	(3.008)	(3.150)	(3.931)	(4.229)
(adj) R^2	0.038	0.162	0.317	0.484	0.613
$w/C \times log(D/P)$	0.059	0.243	0.456	0.654	0.826
t-stat.	(2.992)	(3.083)	(3.358)	(4.769)	(6.221)
(adj) R^2	0.028	0.134	0.264	0.398	0.509

Notes for Table II A: The table shows the result of the predictive regression

$$r_{t,t+K} = \alpha + \beta\,(k)\,\mathbf{x}_t + \varepsilon_{t+K}$$

where $\mathbf{x}_t = w_t/C_t$; or $\log\left(D_t/P_t\right)$, or both; where K is the numbers of quarter ahead and $r_{t,t+K}$ is the cumulative log excess return over K quarters. Number in parenthesis show Newey-West adjusted t-statistics. The sample is 1946:01-1999:04.

TABLE II B

Forecasting Future Returns

Sample: 1948:01 - 1999:04

	Forecasting Horizon				
K	1	4	8	12	16
w/C	-0.342	-1.211	-2.493	-3.761	-4.920
t-stat.	(-2.315)	(-2.548)	(-3.289)	(-3.674)	(-3.761)
(adj) R^2	0.020	0.071	0.165	0.266	0.334
$log(D/P)$	0.023	0.109	0.223	0.333	0.456
t-stat.	(1.425)	(1.689)	(1.486)	(1.550)	(1.736)
(adj) R^2	0.004	0.042	0.091	0.137	0.190
w/C	-0.552	-1.918	-3.485	-4.674	-5.598
t-stat.	(-3.315)	(-3.381)	(-4.500)	(-4.916)	(-4.780)
$log(D/P)$	0.050	0.198	0.359	0.469	0.557
t-stat.	(3.113)	(3.484)	(4.077)	(4.676)	(4.737)
(adj) R^2	0.051	0.196	0.385	0.529	0.617
$w/C \times log(D/P)$	0.065	0.266	0.503	0.685	0.834
t-stat.	(3.130)	(3.303)	(3.744)	(4.844)	(6.063)
(adj) R^2	0.034	0.153	0.303	0.416	0.496

Notes for Table II B: The table shows the result of the predictive regression

$$r_{t,t+K} = \alpha + \beta(k)\,\mathbf{x}_t + \varepsilon_{t+K}$$

where $\mathbf{x}_t = w_t/C_t$; or $\log(D_t/P_t)$, or both; where K is the numbers of quarter ahead and $r_{t,t+K}$ is the cumulative log excess return over K quarters. Number in parenthesis show Newey-West adjusted t-statistics. The sample is 1948:01-1999:04.

TABLE III

Forecasting Future Returns

Sample: 1952:01 - 1994:04

	Forecasting Horizon				
K	1	4	8	12	16
w/C	-0.297	-1.037	-2.124	-3.131	-4.291
t-stat.	(-1.425)	(-1.459)	(-1.979)	(-2.300)	(-2.610)
(adj) R^2	0.007	0.030	0.081	0.145	0.226
$log(D/P)$	0.085	0.347	0.597	0.730	0.779
t-stat.	(3.055)	(3.779)	(3.507)	(3.458)	(3.577)
(adj) R^2	0.043	0.188	0.330	0.404	0.414
w/C	-0.430	-1.428	-2.456	-3.243	-4.128
t-stat.	(-2.143)	(-2.264)	(-3.459)	(-4.260)	(-4.122)
$log(D/P)$	0.098	0.377	0.624	0.740	0.763
t-stat.	(3.496)	(4.221)	(4.539)	(4.532)	(5.014)
(adj) R^2	0.063	0.251	0.443	0.564	0.627
$w/C \times log(D/P)$	0.116	0.438	0.733	0.888	0.966
t-stat.	(3.836)	(4.108)	(5.111)	(6.007)	(7.202)
(adj) R^2	0.067	0.255	0.451	0.566	0.616

Notes for Table III: The table shows the result of the predictive regression

$$r_{t,t+K} = \alpha + \beta(k)\,\mathbf{x}_t + \varepsilon_{t+K}$$

where $\mathbf{x}_t = w_t/C_t$; or $\log(D_t/P_t)$, or both; where K is the numbers of quarter ahead and $r_{t,t+K}$ is the cumulative log excess return over K quarters. Number in parenthesis show Newey-West adjusted t-statistics.

TABLE IV

Forecasting Future Returns

Sample: 1952:01 - 1999:04

	Forecasting Horizon				
K	1	4	8	12	16
w/C	-0.345	-1.218	-2.370	-3.542	-4.687
t-stat.	(-2.324)	(-2.575)	(-3.170)	(-3.595)	(-3.809)
(adj) R^2	0.021	0.074	0.160	0.259	0.354
$log(D/P)$	0.016	0.086	0.177	0.251	0.310
t-stat.	(0.823)	(1.117)	(0.943)	(0.894)	(0.935)
(adj) R^2	-0.002	0.018	0.042	0.056	0.066
w/C	-0.621	-2.175	-3.754	-4.887	-5.786
t-stat.	(-3.463)	(-3.433)	(-4.300)	(-4.720)	(-4.748)
$log(D/P)$	0.061	0.238	0.419	0.522	0.559
t-stat.	(2.856)	(3.059)	(3.263)	(3.475)	(3.689)
(adj) R^2	0.050	0.196	0.365	0.486	0.565
$w/C \times log(D/P)$	0.074	0.309	0.578	0.758	0.862
t-stat.	(2.683)	(2.799)	(3.093)	(3.803)	(4.637)
(adj) R^2	0.029	0.140	0.275	0.359	0.399

Notes for Table IV: The table shows the result of the predictive regression

$$r_{t,t+K} = \alpha + \beta\,(k)\,\mathbf{x}_t + \varepsilon_{t+K}$$

where $\mathbf{x}_t = w_t/C_t$; or $\log{(D_t/P_t)}$, or both; where K is the numbers of quarter ahead and $r_{t,t+K}$ is the cumulative log excess return over K quarters. Number in parenthesis show Newey-West adjusted t-statistics

TABLE V

Fama-French Portfolios: 1946-1998

CAPM Fama-MacBeth Regressions

Panel A

	Const.	R^M	$s^w R^M$	R^w	$s^w R^w$	R^2 [*Adj*]
1	3.90	−1.32				13%
t-stat.	(3.92)	(−1.16)				[10%]
	[3.87]	[−1.15]				
2	3.78	−1.19		−0.20		14%
t-stat.	(3.84)	(−1.07)		(−.54)		[6%]
	[3.75]	[−1.05]		[−0.53]		
3	5.75	−3.30	0.32			48%
t-stat	(5.07)	(−2.72)	(3.19)			[43%]
	[3.36]	[−1.92]	[2.14]			
4	5.52	−3.06	0.34	−0.55		53%
t-stat	(4.87)	(−2.53)	(3.48)	(−1.62)		[47%]
	[2.98]	[−1.66]	[2.16]	[−1.00]		
5	3.94	−1.47		−0.36	−0.05	40%
t-stat	(3.96)	(−1.30)		(−1.01)	(−3.74)	[32%]
	[2.30]	[−0.82]		[−0.60]	[−2.19]	
6	5.22	−2.79	0.27	−0.55	−0.03	58%
t-stat.	(4.81)	(−2.38)	(3.04)	(−1.62)	(−2.75)	[49%]
	[2.99]	[−1.58]	[1.92]	[−1.03]	[−1.75]	

Panel B

	Const.	R^M	s^w	$s^w R^M$	$s^w R^w$	R^2 [*Adj*]
1	6.58	−4.38	3.76			50%
t-stat.	(5.10)	(−3.18)	(2.79)			[45%]
	[3.39]	[−2.21]	[1.87]			
2	6.74	−4.48	2.95	0.18		58%
t-stat	(5.12)	(−3.21)	(2.36)	(2.79)		[52%]
	[3.39]	[−2.23]	[1.58]	[1.90]		
3	6.67	−4.44	3.28	0.18	−0.74	68%
t-stat	(5.07)	(−3.18)	(2.62)	(2.77)	(−2.70)	[61%]
	[2.94]	[−1.96]	[1.54]	[1.66]	[−1.60]	

Notes to Table V: See Notes for Table VII.

TABLE VI

Fama-French Portfolios: 1963-1998

CAPM Fama-MacBeth Regressions

Panel A

	Const.	R^M	$s^w R^M$	R^w	$s^w R^w$	R^2 [*Adj*]
1	2.80	−0.46				2%
t-stat.	(2.94)	(−0.38)				[−2%]
	[2.93]	[−0.38]				
2	2.35	0.00		−0.32		3%
t-stat.	(2.54)	(0.00)		(−1.01)		[-0%]
	[2.43]	[0.00]		[−0.97]		
3	3.90	−1.89	0.34			51%
t-stat	(3.86)	(−1.55)	(2.97)			[46%]
	[2.73]	[−1.20]	[2.14]			
4	2.76	−0.76	0.36	−0.79		60%
t-stat	(2.88)	(−0.64)	(3.07)	(−2.74)		[55%]
	[1.74]	[−0.44]	[1.89]	[−1.71]		
5	3.79	−1.77		−0.30	−0.04	36%
t-stat	(3.40)	(−1.37)		(−0.94)	(−2.90)	[27%]
	[1.99]	[−0.89]		[−0.57]	[−1.72]	
6	3.10	−1.14	0.32	−0.73	−0.01	62%
t-stat.	(3.04)	(−0.93)	(3.11)	(−2.42)	(−1.48)	[54%]
	[1.89]	[−0.65]	[1.99]	[−1.55]	[−0.94]	

Panel B

	Const.	R^M	s^w	$s^w R^M$	$s^w R^w$	R^2 [*Adj*]
1	5.10	−3.26	3.90			45%
t-stat.	(4.12)	(−2.29)	(2.62)			[40%]
	[2.95]	[−1.75]	[1.90]			
2	4.65	−2.78	2.53	0.22		56%
t-stat	(3.98)	(−2.04)	(1.95)	(2.92)		[49%]
	[2.94]	[−1.61]	[1.46]	[2.23]		
3	3.56	−1.72	1.75	0.23	−0.77	68%
t-stat	(3.24)	(−1.31)	(1.37)	(2.99)	(−3.34)	[61%]
	[2.07]	[−0.92]	[0.89]	[1.99]	[−2.20]	

Notes to Table VI: See Notes for Table VII.

TABLE VII
Fama-French Portfolios: 1963-1998
CAPM Fama-MacBeth Regressions
The Case of Lagged Labor Income

Panel A

	Const.	R^M	$s^w R^M$	R^w	$s^w R^w$	R^2 [*Adj*]
1	2.80	−0.46				2%
t-stat.	(2.94)	(−0.38)				[−2%]
	[2.93]	[−0.38]				
2	4.49	−2.36		0.94		24%
t-stat.	(3.93)	(−1.82)		(2.01)		[17%]
	[2.84]	[−1.42]		[1.46]		
3	3.90	−1.89	0.34			51%
t-stat	(3.86)	(−1.55)	(2.97)			[46%]
	[2.73]	[−1.20]	[2.14]			
4	4.24	−2.26	0.31	0.28		51%
t-stat	(3.86)	(−1.76)	(3.42)	(0.75)		[45%]
	[2.79]	[−1.38]	[2.54]	[0.55]		
5	2.65	−0.69		0.48	−0.07	60%
t-stat	(2.90)	(−0.60)		(1.25)	(−3.82)	[54%]
	[1.29]	[−0.32]		[0.57]	[−1.72]	
6	3.01	−1.08	0.23	0.28	−0.06	64%
t-stat.	(3.10)	(−0.91)	(2.88)	(0.75)	(−3.42)	[57%]
	[1.65]	[−0.56]	[1.62]	[0.41]	[−1.85]	

Panel B

	Const.	R^M	s^w	$s^w R^M$	$s^w R^w$	R^2 [*Adj*]
1	5.10	−3.26	3.90			45%
t-stat.	(4.12)	(−2.29)	(2.62)			[40%]
	[2.95]	[−1.75]	[1.90]			
2	4.65	−2.78	2.53	0.22		56%
t-stat	(3.98)	(−2.04)	(1.95)	(2.92)		[49%]
	[2.94]	[−1.61]	[1.46]	[2.23]		
3	4.53	−2.68	2.80	0.22	−0.26	56%
t-stat	(2.74)	(−1.49)	(1.68)	(2.14)	(−0.78)	[48%]
	[2.74]	[−1.49]	[1.68]	[2.15]	[−0.79]	

Notes for Tables V, VI and VII: The tables present estimates of cross-sectional Fama-MacBeth regressions using the 25 Fama-French portfolios. In parenthesis we report the uncorrected Fama-MacBeth $t-$statistic. The Shanken (1992) corrected $t-$statistic are reported in brackets. The unadjusted and adjusted (in brackets) R^2 are reported in the last column. $s^w R^M$ denotes the component of $s^w R^M$ orthogonal to R^M. Similarly $s^w R^w$ denotes the component of $s^w R^w$ orthogonal to R^w. Panel A reports the specifications that are supported by the model introduced in section II. Panel B reports results where the variable s^w is introduced independently.

Table V shows the results for the sample period 1946-1998. Table VI shows the results for the sample period 1963-1998. Table VII shows the results for the sample period 1963-1998 and using the dating convention advocated by Jagannathan and Wang (1996).

TABLE VIII

CCAPM Fama-MacBeth Regressions

Panel A: Sample 1946-1998

	Const.	Δc	s^w	$s^w \times \Delta c$	R^2 [*Adj*]
1	2.27	0.05			0%
t-stat.	(3.32)	(0.15)			[0%]
	[3.31]	[0.15]			
2	3.40	-0.27	1.66		7%
t-stat.	(4.65)	(-0.94)	(1.60)		[0%]
	[4.00]	[-0.81]	[1.39]		
3	2.37	-0.01		0.00	0%
t-stat.	(3.65)	(-0.05)		(0.23)	[0%]
	[3.64]	[-0.05]		[0.23]	
4	3.49	.22	2.43	-0.02	14%
t-stat.	(4.69)	(0.83)	(2.08)	(-1.83)	[2%]
	[3.21]	[0.57]	[1.44]	[-1.26]	

Panel B: Sample 1963-1998

	Const.	Δc	s^w	$s^w \times \Delta c$	R^2 [*Adj*]
1	1.63	0.18			5%
t-stat.	(2.15)	(0.61)			[1%]
	[2.07]	[0.58]			
2	3.27	-0.18	2.72		22%
t-stat.	(3.85)	(-0.67)	(2.23)		[15%]
	[3.13]	[-0.55]	[1.84]		
3	1.94	0.05		0.01	6%
t-stat.	(2.78)	(0.26)		(0.74)	[0%]
	[2.72]	[0.26]		[0.73]	
4	3.63	0.14	3.13	-0.02	39%
t-stat.	(3.90)	(0.74)	(2.40)	(-2.08)	[30%]
	[2.50]	[0.49]	[1.57]	[-1.35]	

Notes for Table VIII: This table presents estimates of cross-sectional Fama-MacBeth Regressions using the 25 Fama-French portfolios. In parenthesis we report the uncorrected Fama-MacBeth $t-$statistic. The Shanken (1992) corrected $t-$statistic are reported in brackets. The unadjusted and adjusted (in brackets) R^2 are reported in the last column. Δc denotes consumption growth, s^w is the share of labor income to consumption, $s^w \times \Delta c$ denotes the component of consumption growth scaled by the share of labor income to consumption that is orthogonal to Δc.

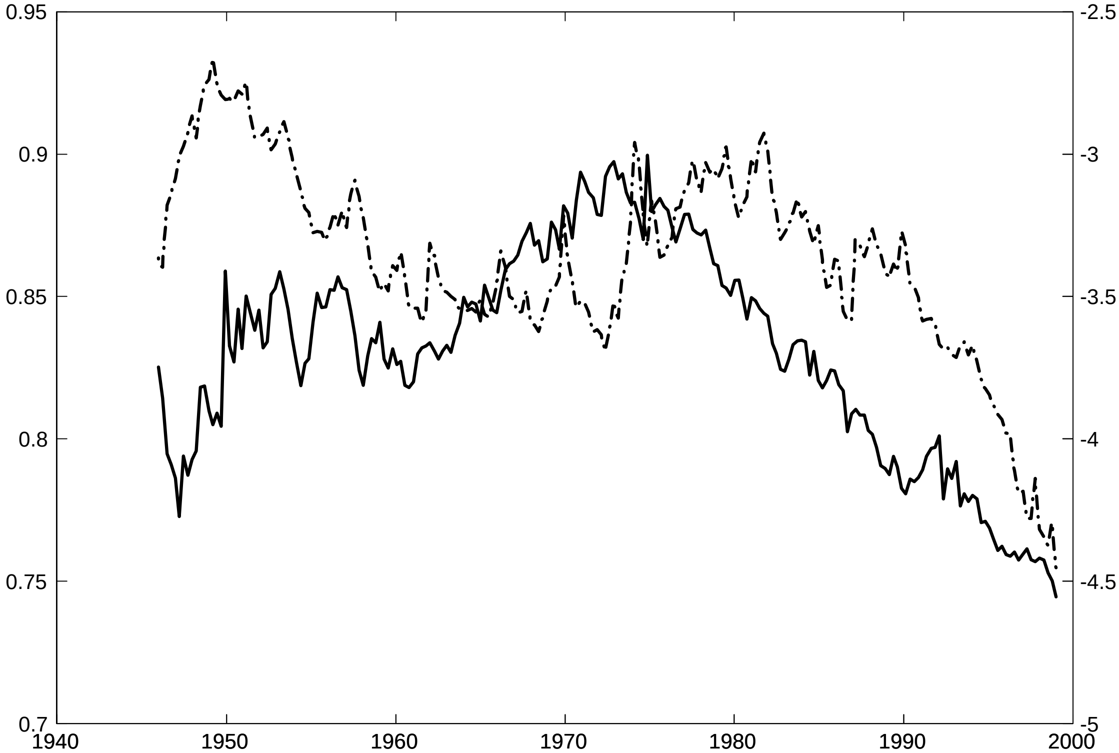
TABLE IX

Simulated Coefficients for Spurious Regression

		Percentiles								
K	x_t	1%	2.5%	5%	10%	50%	90%	95%	97.5%	99%
1	s^w	-0.469	-0.381	-0.309	-0.225	-0.003	0.208	0.282	0.349	0.441
4	”	-1.879	-1.507	-1.189	-0.888	-0.019	0.8186	1.108	1.366	1.663
8	”	-3.642	-2.914	-2.322	-1.753	-0.029	1.6196	2.163	2.608	3.198
12	”	-5.186	-4.228	-3.435	-2.577	-0.071	2.3876	3.165	3.865	4.717
16	”	-6.705	-5.405	-4.441	-3.356	-0.076	3.1034	4.119	5.073	6.138
1	$\ln(\frac{D}{P})$	-0.008	-0.005	-0.003	0.0007	0.016	0.0466	0.059	0.073	0.087
4	”	-0.033	-0.021	-0.010	0.003	0.063	0.182	0.230	0.277	0.329
8	”	-0.07	-0.043	-0.021	0.0056	0.128	0.3495	0.434	0.516	0.611
12	”	-0.109	-0.067	-0.034	0.0081	0.191	0.5011	0.613	0.709	0.845
16	”	-0.149	-0.095	-0.049	0.0096	0.251	0.6381	0.765	0.884	1.014
1	$\ln(\frac{D}{P})$	-0.008	-0.005	-0.002	0.0016	0.019	0.0551	0.07	0.085	0.102
	s_w	-0.628	-0.517	-0.424	-0.325	-0.029	0.2725	0.363	0.455	0.578
4	”	-0.033	-0.021	-0.007	0.006	0.078	0.2108	0.265	0.316	0.375
	”	-2.317	-1.941	-1.615	-1.245	-0.112	1.0356	1.396	1.740	2.162
8	”	-0.072	-0.042	-0.017	0.012	0.1529	0.3979	0.487	0.571	0.666
	”	-4.35	-3.633	-3.034	-2.346	-0.205	1.9677	2.61	3.225	4.004
12	”	-0.11	-0.068	-0.026	0.0151	0.2241	0.5579	0.672	0.772	0.886
	”	-6.071	-5.066	-4.233	-3.304	-0.307	2.7667	3.672	4.498	5.573
16	”	-0.155	-0.089	-0.038	0.017	0.292	0.6995	0.828	0.936	1.059
	”	-7.535	-6.311	-5.318	-4.129	-0.369	3.5187	4.636	5.703	7.017
1	$\ln\left(\frac{D}{P}\right) \times s^w$	-0.023	-0.019	-0.014	-0.009	0.017	0.0606	0.077	0.092	0.110
4	”	-0.095	-0.075	-0.056	-0.035	0.068	0.2257	0.280	0.334	0.392
8	”	-0.187	-0.15	-0.111	-0.067	0.137	0.421	0.514	0.594	0.697
12	”	-0.277	-0.226	-0.165	-0.094	0.202	0.5878	0.705	0.804	0.925
16	”	-0.371	-0.291	-0.215	-0.120	0.269	0.7281	0.865	0.971	1.119

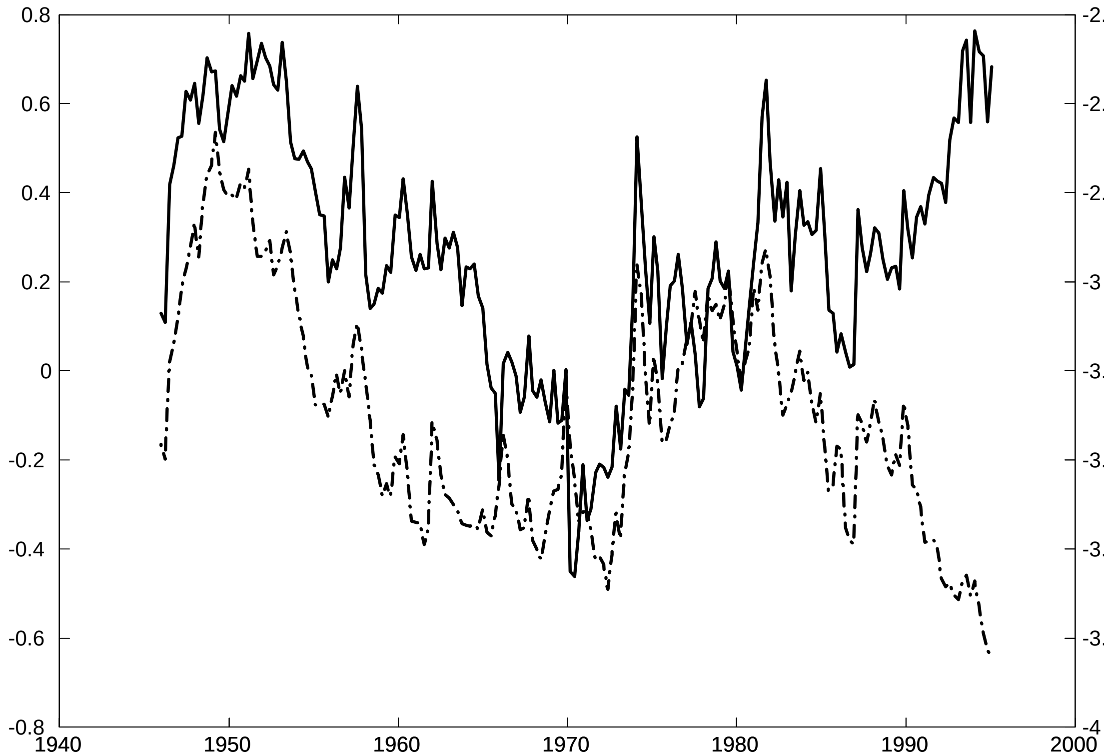
Notes for Table IX: The table shows the distribution of predictive regression coefficients obtained from 10,000 simulations of the system $y_t = a + u_t$, $x_t = \alpha + \phi x_{t-1} + v_t$ where for each simulation, a K period ahead OLS regression is performed. That is, $y_t(K) = \sum_{i=1}^{K} y_{t+i}$ is regressed on x_{t-1}. The parameters a, α and ϕ as well as $\Sigma = E(\varepsilon_t, \varepsilon_t')$ with $\varepsilon_t = (u_t, v_t)'$ are given by their real sample estimates for each regressor x_t as in the table.

Figure 1: Log Dividend Price Ratio and Labor Income to Consumption Ratio



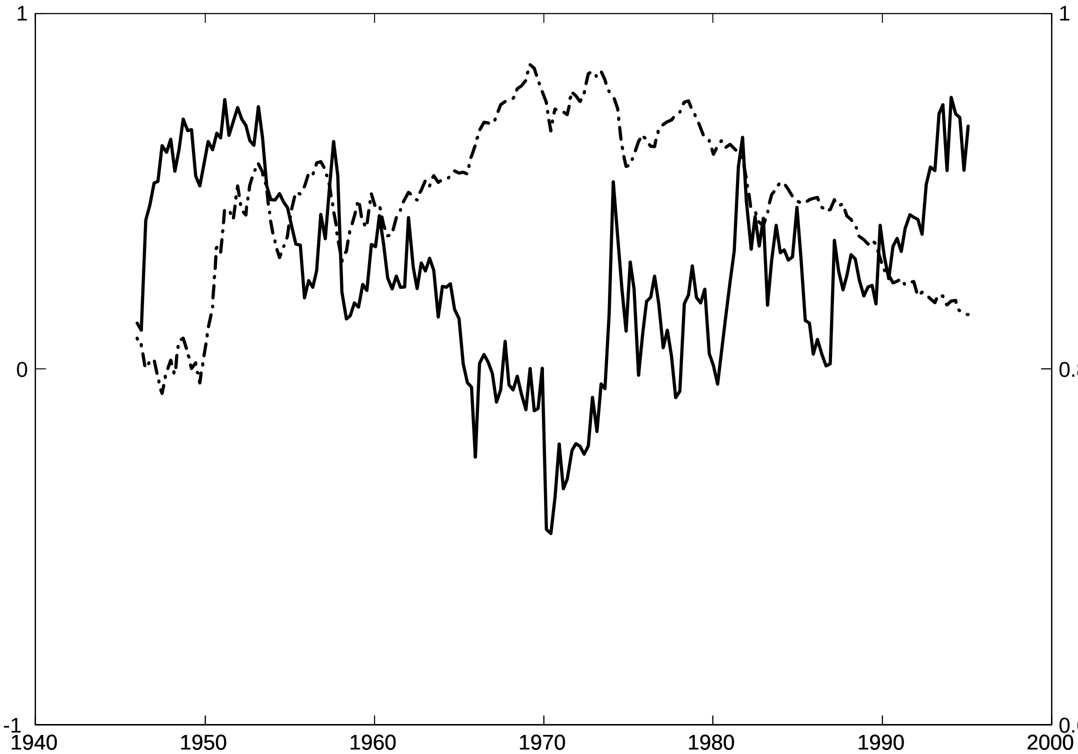
The time series of the labor income - to - consumption ratio (solid line) and of the log dividend price ratio (dash-dotted line).

Figure 2: Long-term Return and Log Dividend Price Ratio



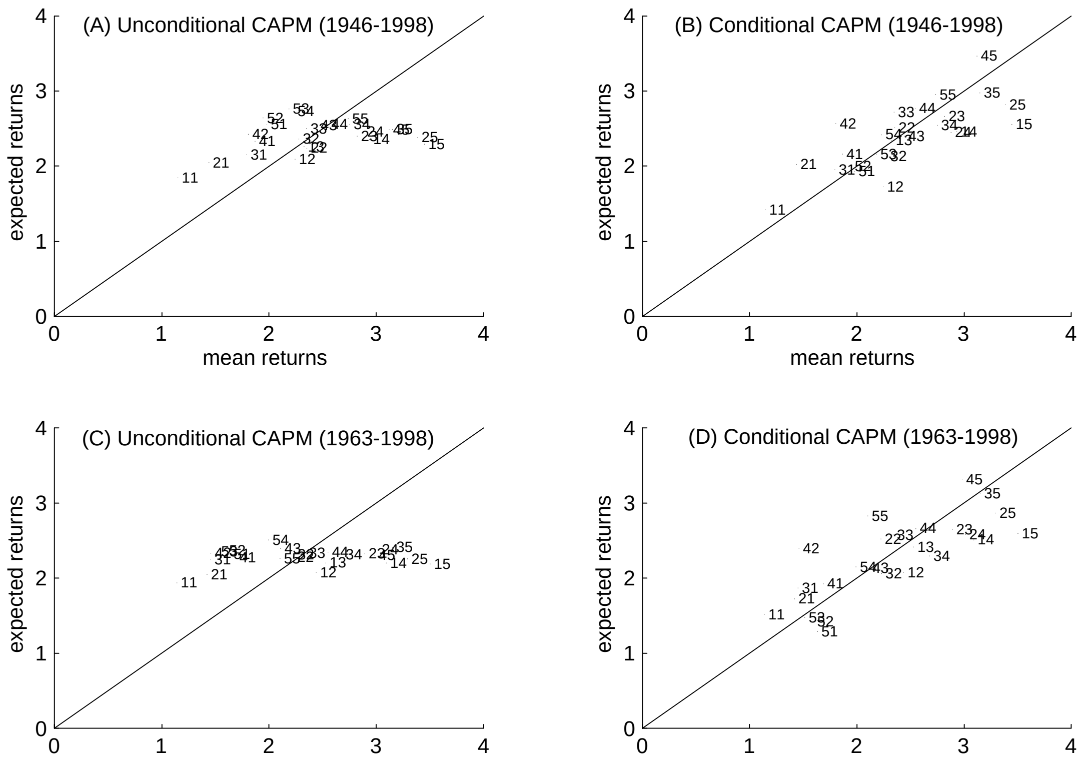
This figure plots the 4 year cumulative return (solid line) lagged by 4 years and the current log dividend price ratio (dash-dotted line)

Figure 3: Long-term Return and Labor Income to Consumption Ratio



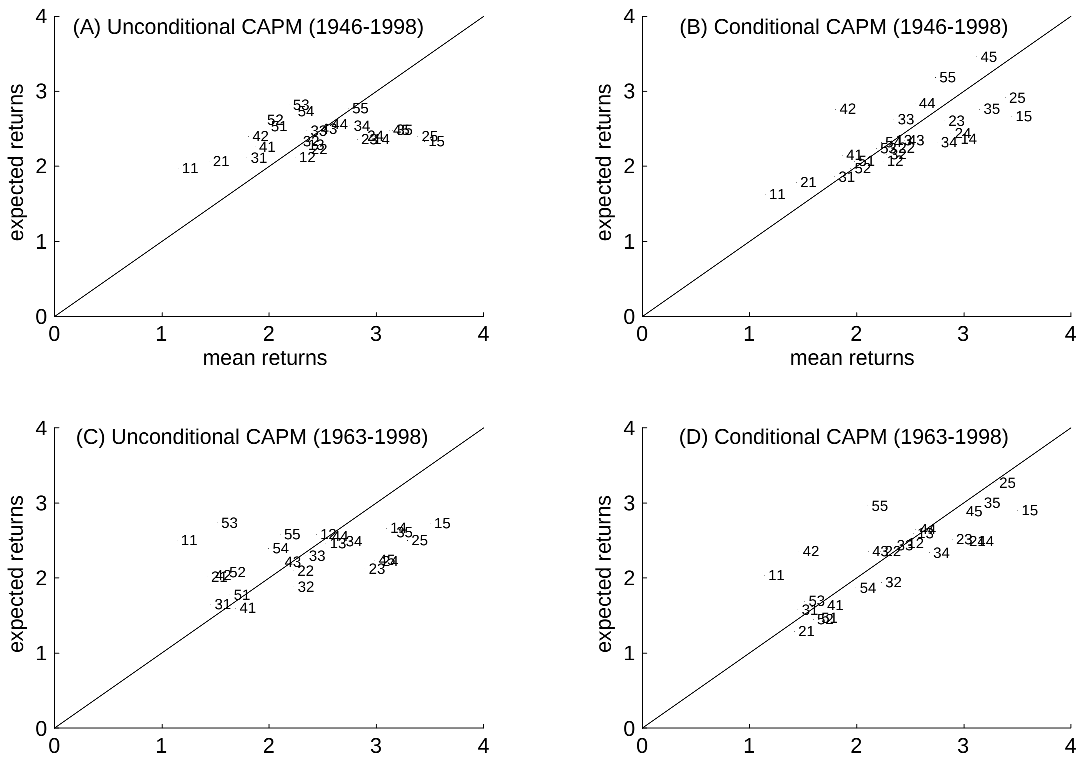
This figure plots the 4 year cumulative return (solid line) lagged by 4 years and the current labor income to consumption ratio (dash-dotted line)

Figure 4: Conditional CAPM



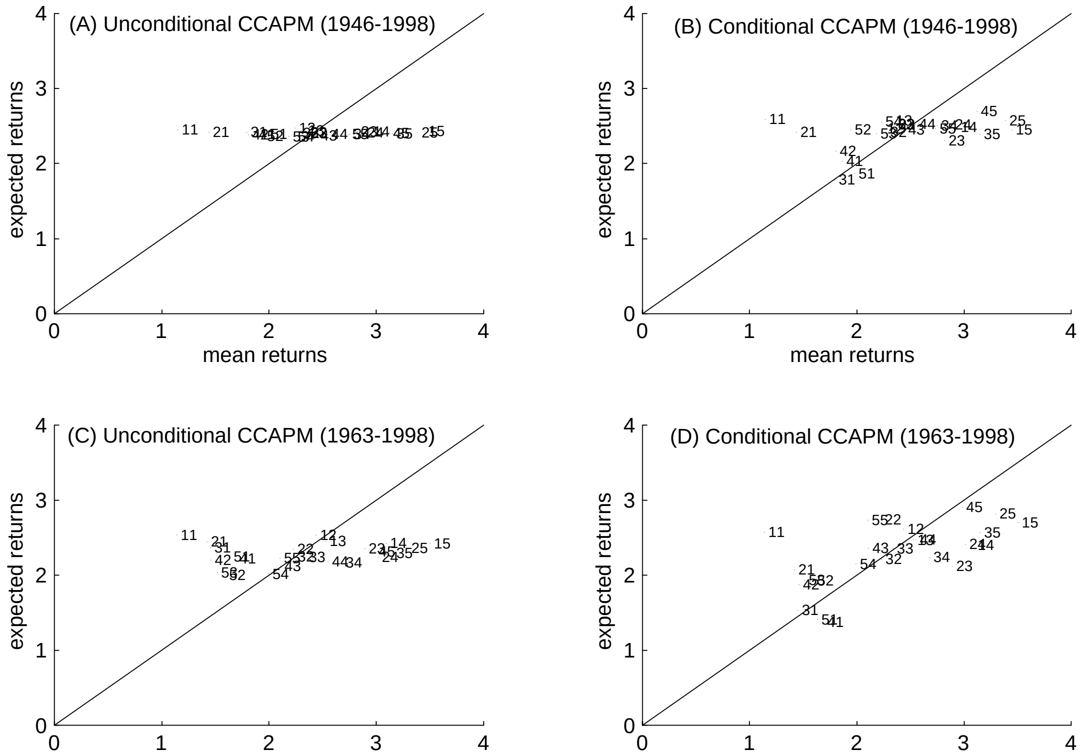
These four plots show the realized versus fitted returns on the 25 FF portfolios. Panel A and C shows the unconditional CAPM augmented by labor income for the sample periods 1946-1998 and 1963-1998, respectively (regressions 2 in Panel A of Tables V and VI). Panel B and C shows the conditional CAPM, where the interaction terms $R_t^M \times s_t^w$ and $R_t^w \times s_t^w$ are included (regressions 6 in Panel A of Tables V and VI).

Figure 5: Conditional CAPM with Lagged Labor Income



These four plots show the realized versus fitted returns on the 25 FF portfolios when labor income growth is lagged one quarter. Panel A and C shows the unconditional CAPM augmented by labor income for the sample periods 1946-1998 and 1963-1998, respectively (regressions 2 in Panel A of Tables VII. The regression for 1946-1998 is not explicitly reported in Tables). Panel B and C shows the conditional CAPM, where the interaction terms $R_t^M \times s_t^w$ and $R_t^w \times s_t^w$ are included (regressions 6 in Panel A of Tables VII. The regression for 1946-1998 is not explicitly reported in Tables).

Figure 6: Conditional C-CAPM



These four plots show the realized versus fitted returns on the 25 FF for the Consumption CAPM. Panel A and C shows the unconditional C-CAPM for the sample periods 1946-1998 and 1963-1998, respectively. Panel B and C shows the conditional C-CAPM, when the factor s_t^w and the interaction terms $\Delta c_t \times s_t^w$ and $R_t^w \times s_t^w$ are included (regressions 4 in Panels A and B of Table VIII).