Consumption, Dividends, and the Cross-Section of Equity Returns

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September, 2001

Abstract

A central economic idea is that an asset's risk premium is determined by its ability to insure against fluctuations in consumption (i.e., by consumption beta). Consistent with this intuition, we show that a model with constant consumption betas does extremely well in capturing cross-sectional differences in risk premia. More specifically, we present a dynamic general equilibrium model where cross-sectional differences in an asset's consumption beta are determined by cross-sectional differences in the exposure of the asset's dividends to aggregate consumption – that is, by the consumption leverage of the asset's dividends. We measure this consumption leverage in one case as the stochastic cointegration parameter between dividends and consumption, and in another, by the covariance of ex-post dividend growth rates with expected consumption growth rate. Cross-sectional differences in this consumption leverage parameter can explain up to 65% of the cross-sectional variation in risk premia across 31 portfolios—which include the market, 10 momentum-, 10 size-, and 10 book-to-market-sorted portfolios. The consumption leverage model can justify much of the observed value, momentum, and size risk premium spreads. For this asset menu, empirical three factor models (size, BM, and market factors, for example) can justify about 17% of the cross-sectional differences in risk premia. Time varying beta asset pricing models also have considerable difficulty justifying the cross-section of risk premia for these assets.

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1 Introduction

The idea that differences in exposure to systematic risk should justify differences in risk premia across assets is central to asset pricing. Sharpe (1964), Lintner (1965), and Black (1972) show that assets' exposures to aggregate wealth should determine cross-sectional differences in risk premia. The influential work of LeRoy (1973), Lucas (1978), and Breeden (1979) underscores the intuition that the risk premium on an asset is determined by its ability to insure agents' consumption in the economy. Consequently, the exposure of an asset to consumption fluctuations (i.e., the consumption beta) should determine cross-sectional differences in risk premia. Empirically, however, neither of these approaches seems to do well in explaining cross-sectional variation in observed risk premia. Hansen and Singleton (1982, 1983), and a wide array of subsequent papers[1], show that parametric versions of consumption based models have great difficulty in capturing risk premia across assets. Given these difficulties, Fama and French (1993) (FF) provide an empirical specification where differences in the cross-section of risk premia are related to size, book-to market, and market portfolio risk factors. This specification can be motivated via Ross (1976)'s Arbitrage Pricing Theory.

In this paper, we show that the intuition provided by the consumption based models does extremely well in explaining cross-sectional variation in risk premia. Our focus will be 10 size, 10 book-to-market, and 10 momentum sorted portfolios, as well as the market portfolio itself (31 in all). More specifically, we present a dynamic general equilibrium model which provides a precise mapping from the consumption leverage (exposure to aggregate consumption) of the asset's dividends to an asset's constant consumption beta. Dividend cash flows which have larger consumption leverage must, as shown in the paper, also carry a higher risk premium. We show that the cross-sectional dispersion in this degree of consumption leverage (and hence the consumption beta) explains up to 70% of the cross-sectional variation in observed risk premia. Further, the estimated market price of consumption risk is sizable and positive in all cases. Our estimated model can duplicate much of the spread in the mean returns of the extreme momentum portfolios (winner minus loser), the size spread (small capitalization minus large), and the value spread (high book-to-market minus low). For the same collection of assets, the benchmark FF factor model can explain only about 17% of the cross-sectional differences in the risk premia. This is primarily due to our inclusion of the challenging

[1] For an extensive recent survey see Campbell (2000). In addition, Fama and French (1993), Jagannathan and Wang (1996), and others also demonstrate the empirical failings of the static market based CAPM.

momentum portfolios in the asset menu. Our motivation for the choice of these 31 portfolios is that they form the basis of common risk factors typically relied upon to explain cross-sectional differences in risk premia (see Fama and French (1993) and Carhart (1997), for example).

We measure the exposure of a portfolio's dividend stream to consumption (consumption leverage) in the time-series via the stochastic cointegrating relationship between portfolio dividends and aggregate consumption (for the notion of stochastic cointegration, see Campbell and Perron (1993) and Ogaki and Park (1998)). The stochastic cointegration regression entails a time series regression of the log level of the dividends on a constant, a deterministic time trend, and the log level of consumption; the parameter estimate on the log level of aggregate consumption is the stochastic cointegration parameter and the consumption leverage parameter, which we use to explain the cross-sectional differences in risk premia. Additionally, we also entertain the possibility that consumption and dividends are not stochastically cointegrated. In this case, we measure the consumption leverage, consistent with the dynamic general equilibrium model, by the projection coefficient of future ex-post dividend growth rate on the current expected aggregate consumption growth rate. Given the consumption leverage, we rely on the dynamic general equilibrium to map this into the consumption beta of the asset. As argued in Campbell and Mei (1993)) an asset's beta is not exogenous, but is intimately related to underlying cash flows. Our approach of deriving the asset's consumption beta via the relationship between dividends and consumption makes the origins of the consumption beta clear.

To compare our empirical results to alternative models, we also report results on the three factor FF model, and market and human capital augmented versions of the CAPM. We also report results for the time-varying beta specifications of the market and human capital augmented CAPM (Jagannathan and Wang (1996)) and the consumption based C-CAPM specification considered in Lettau and Ludvigson (2001b). The constant consumption beta, based on consumption leverage developed in the paper can capture about 70% of the cross-sectional variation in risk premia on the monthly and about 65% on the annual frequency. In general, beta's associated with unconditional factor models cannot explain the cross-sectional variation in observed risk premia. However, certain specifications that permit time-varying beta's do somewhat better. The time-varying consumption β model considered in Lettau and Ludvigson (2001b) captures roughly 15% of the cross-sectional return variation for data measured at both monthly and annual frequencies. The human capital augmented CAPM (see Jagannathan and Wang (1996) and Campbell (1996)) with time-varying beta's explains about 40% of the cross sectional variation at an annual frequency. While these specifications generally do somewhat better than their unconditional counterparts, the signs and significance of the estimated risk prices vary across specifications and data frequency, making economic interpretation somewhat difficult. In addition, these specifications typically do not provide the mapping from the relationship between risk sources and cash flows to time-varying asset betas.

In all, our empirical evidence suggests that there is a small predictable and fairly persistent component in aggregate consumption growth rates. Small changes in this predictable component have long lasting effects on asset valuation (see Barsky and DeLong (1993) and Bansal and Lundblad (2000)) and equilibrium asset returns (see Bansal and Yaron (2000)). Dividends on different assets have different exposures to this predictable component in consumption, which represents the non-diversifiable risk in the economy; quantifiable differences in this exposure determine the consumption leverage and asset beta, and consequently the cross-section of risk premia. We show that the strong empirical support for the consumption leverage model is consistent with this economic interpretation.

Section 2 provides the solution for the consumption leverage model, as well as an analytical expression for the fundamental consumption beta (risk exposure). Section 3 provides data description and empirical evidence for the degree of stochastic cointegration between portfolio dividends and aggregate consumption. Section 4 details the ability of the consumption leverage model to explain cross-sectional variation in risk premia in comparison to standard factor and consumption based models. Finally, Section 5 concludes.

2 Modeling Asset Returns

2.1 Preferences

In this section, we present a dynamic general equilibrium model which relates an asset's consumption beta, and the hence the asset's risk premium, to the fundamental relation between dividends and consumption. First, consider the preference specification that facilitates the separation of the intertemporal elasticity of substitution and risk aversion in Epstein and Zin (1989) and Weil (1990):

$$U_t = \left\{ (1-\delta)\, C_t^{\frac{1-\gamma}{\theta}} + \delta \left(E_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}} \tag{1}$$

where δ is a time preference parameter, ψ denotes the intertemporal elasticity of substitution, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, where γ represents the coefficient of relative risk aversion.[2] At date t, the wealth of the agent is W_t, and we can write the budget constraint of the agent as follows:

$$(W_t - C_t) * R_{c,t+1} = W_{t+1} \tag{2}$$

where $W_t - C_t$ is the amount of capital invested in the asset market, and $R_{c,t}$ is the return on the portfolio that pays the aggregate dividend stream. Under the preferences in (1), Epstein and Zin (1989) show that the Intertemporal Marginal Rate of Substitution (IMRS) is

$$M_{t+1} = \delta^{\theta} G_{t+1}^{-\frac{\theta}{\psi}} (1 + R_{c,t+1})^{-(1-\theta)} \tag{3}$$

where G_{t+1} is the aggregate gross growth rate of consumption and $R_{c,t+1}$ is the return on the asset that in each period delivers aggregate consumption. All asset returns in this economy must satisfy the standard asset pricing condition that

$$E_t[M_{t+1} R_{i,t+1}] = 1 \tag{4}$$

The one step ahead innovation in the log of the IMRS (that is, $\ln(M_{t+1}) - E_t[\ln(M_{t+1})]$), is given by

$$\eta_{M,t+1} = -\frac{\theta}{\psi}\eta_{t+1} - (1-\theta)\eta_{c,t+1} \tag{5}$$

where η_{t+1} is the innovation in aggregate consumption growth and $\eta_{c,t+1}$ is the innovation in the return $r_{c,t+1}$. Risk premia are determined by computing an asset return's covariance with the innovation in equation (5). It is well recognized that $r_{c,t+1}$ is endogenous to the model (see Cochrane and Hansen (1992)), and the innovation $\eta_{c,t+1}$, as shown below, depends only on the consumption growth innovation, η_{t+1}. Hence, all risk premia are determined by the assets' exposures to the uncertainty in aggregate consumption.

[2] The representative agent's budget constraint can also be stated as:

$$C_t + P_t' h_{t+1} = D_t' h_t + P_t' h_t \equiv W_t$$

where P_t is a vector of asset prices that pay a dividend stream of D_{t+j} for $j = 1, \ldots, \infty$. h_t is a vector of asset holdings at the end of time period $t-1$. Note that, as in Campbell (1996), we assume that the labor income of the agent is a traded asset that is included in the asset holdings. This ensures that the aggregate consumption will equal financial market dividends plus labor income.

2.2 Aggregate Consumption

We refer the log of aggregate consumption as c, we will assume that teh log level of consumption follows an ARIMA(1,1,1) process. [3] Beveridge and Nelson (1981) show that the univariate process for c_t can be stated as the sum of a deterministic trend, a stochastic trend (permanant componant), and a stationary component. We refer to η_t as the consumption news at time t, as the aggregate consumption is modeled as an univariate process, this also represents the economic uncertainty.

The growth rate of consumption, given that the level is an ARIMA(1,1,1), $g_{t+1} = c_{t+1} - c_t$, can then be represented as an ARMA(1,1),

$$g_{t+1} = \mu_c(1-\rho) + \rho g_t + \eta_{t+1} - \omega\eta_t \tag{6}$$

where g_t is stationary, and consequently, ρ and ω are less than one in absolute value. The above growth rate process can be stated in terms of x_t, a variable that determines the conditional mean of the consumption growth rate:

$$x_t = (\rho-\omega)\frac{g_t}{(1-\omega L)} \tag{7}$$

$$g_{t+1} = \mu_c + (x_t - \mu_x) + \eta_{t+1}, \tag{8}$$

where $\mu_x = \mu_c\frac{(\rho-\omega)}{(1-\omega)}$ is the unconditional mean of x. Substituting equation (8) into (7), it follows that x_t evolves as an AR(1) process,

$$x_{t+1} = (1-\rho)\mu_x + \rho x_t + (\rho-\omega)\eta_t \tag{9}$$

From equation (7), it is evident that x_t is proportional to an exponential weighted average of the past growth rates.[4]

[3] In the context of the market based static-CAPM, Bansal and Lundblad (2000) show that the ARMA(1,1) specification for growth rates has considerable cross-country support. They show that the small but persistent predictable component in growth rates in conjunction with market risk premium shocks can justify cross country return volatility and cross-correlation.

[4] Using equation (7), it follows that $x_t = (\rho-\omega)\frac{g_t}{(1-\omega L)} = \frac{(\rho-\omega)}{(1-\omega)}[\frac{(1-\omega)}{(1-\omega L)}]g_t$, the second equality shows that x is proportional to an exponentially weighted average of the growth rate.

2.3 Equilibrium

The equilibrium for the above economy is provided in Epstein and Zin (1989). The general equilibrium model presented below relates to that developed in Bansal and Yaron (2000). Using the standard Campbell and Shiller (1988) approximation for the return, we derive the fundamental solution for the log price of consumption stream to consumption ratio, $\ln(P_{c,t}/C_t) = z_{c,t}$. In the appendix, it is shown that the solution for $z_{c,t}$ given the above consumption process is as follows:

$$z_{c,t} = \bar{z}_c + \frac{1-\frac{1}{\psi}}{(1-\kappa_{c,1}\rho)}[x_t - \mu_x] \quad (10)$$

$$z_{c,t+1} - E_t[z_{c,t+1}] = \frac{1-\frac{1}{\psi}}{(1-\kappa_{c,1}\rho)}[(\rho-\omega)\eta_{t+1}] \quad (11)$$

and the innovation in the return $r_{c,t+1}$ is

$$r_{c,t+1} - E_t[r_{c,t+1}] = B_c\eta_{t+1} \quad (12)$$

$$B_c = [1 + \kappa_{c,1}\frac{1-\frac{1}{\psi}}{(1-\kappa_{c,1}\rho)}] \quad (13)$$

Substituting equation (12) into the innovation for the IMRS, leads to the

$$-\eta_{M,t+1} = -[-\frac{\theta}{\psi} - (1-\theta)B_c]\eta_{t+1} \equiv B_M\eta_{t+1} \quad (14)$$

where $B_M = [\frac{\theta}{\psi} + (1-\theta)B_c]$. The risk premium on any asset, where the return and the IMRS are log-normally distributed, satisfy $E_t[r_{i,t+1} - r_{f,t}] = -var_t(r_{i,t+1})/2 + cov_t(-\eta_{M,t+1}, r_{i,t+1})$. The term $var_t(r_{i,t+1})/2$ is the Jensen's inequality effect, and shifting this term to the left hand side leads to the usual arithmetic risk premium restriction:

$$E_t[R_{i,t+1} - R_{f,t}] = \beta_i[B_M\sigma_\eta^2] \quad (15)$$

where,

$$\beta_i = \frac{cov_t(r_i, \eta)}{\sigma_\eta^2} \quad (16)$$

The risk premium on an asset that has an exposure of η_{t+1} to consumption innovation risk, equals $B_M\sigma_\eta^2$, the market price of consumption uncertainty risk. Throughout, it is assumed that B_M is positive, reflecting the fact that the market price of consumption uncertainty is positive. The parameter B_M is determined by the agent's preferences and the parameters that determine consumption growth, as shown above.

In general equilibrium, the risk premium on any asset will depend on preferences, the dynamics of aggregate consumption, and the dynamics of the dividend process associated with the asset under consideration. The variable x that governs the evolution of the conditional mean of consumption growth will be an important state variable in determining the volatility and risk premium on all assets. It is important to note that the β of an asset is not an exogenous variable, but determined in equilibrium by the exposure of the underlying dividends to aggregate consumption risk. In what follows, we derive an analytical expression for an asset's β, providing links to the exposure of the asset's cash flow to aggregate consumption. In particular, we will exploit this connection in our empirical exercise. The cross-section of risk premia are related to assets' β's, which in turn are determined by the exposure of the assets' dividends to aggregate consumption.

Before we derive the risk premium on all assets, we first characterize the dynamic relationship between consumption and dividends. This relationship is important in determining the exposure of different assets to consumption risk, and hence their risk premia.

2.4 Consumption Leverage Model

Abel (1999) argues that the risk premium on different assets can be viewed as a result of differences in their consumption leverage. He considers risk premia on assets where dividends (in logs) are expressed as $d_{i,t} = \phi_i c_t$; ϕ_i is the leverage of the asset. Assets with ϕ larger than one should have larger risk premia than the consumption risk premia, and assets with negative leverage potentially reflect negative risk premia. To begin with, we measure this leverage via stochastic cointegration.

It is well recognized that if two variables are cointegrated, then modeling their growth rates directly leads to loss of information. We specify the dynamics for asset-specific real log cash flows, $d_{i,t}$, in relation to log consumption, c_t:

$$d_{i,t+1} = \mu_i + \delta_i \cdot (t+1) + \phi_i c_{t+1} + \epsilon_{i,t+1} \tag{17}$$

where ϕ_i describes their long-run stochastic relationship and measures the consumption leverage of the asset. It is assumed that $d_{i,t}$ and c_t are I(1), but stationary departures from this relationship, $\epsilon_{i,t}$, are I(0). This specification implies that asset-specific cash flows and aggregate consumption are *stochastically cointegrated*; that is, asset cash flows share a common permanent component with aggregate consumption controlling for a deterministic relationship embodied in δ_i. Note that the inclusion of the term $\delta_i \cdot (t+1)$ allows for the deterministic trends in the dividends to be different from that in the level of consumption. Differently stated, the stochastic cointegration parameter ϕ_i can also me measured by first removing a determistic time trend from the level of both c and d_i and then utilizing the resulting detrended series for measuring ϕ_i. The notion of stochastic cointegration says that $d_{i,t+1} - \mu_i - \phi_i c_{t+1} = \delta_i \cdot (t+1) + \epsilon_{i,t+1}$, may contain only a deterministic trend and a stationary component. It is well recognized (see Ogaki and Park (1998)) that the parameter ϕ_i captures a *stochastic* trend relationship, even in the presence of stationary and correlated measurement errors in c_t and $d_{i,t}$. Further, this parameter, as emphasized in Engle and Granger (1987) and Stock (1987), is superconsistent; that is, converges to its population value at a rate faster than $\sqrt{T}$.

While the common trend specification describes a long-run relationship, the fundamental solution for prices will be specified in terms of growth rates:

$$d_{i,t+1} - d_{i,t} = g_{i,t+1} = \delta_i + \phi_i g_{t+1} + \epsilon_{i,t+1} - \epsilon_{i,t} \tag{18}$$

It can be seen that δ_i facilitates a portfolio specific average rate of growth, and ϕ_i is essentially determined by the exposure of $d_{i,t}$ to the stochastic trend component in c_t. Substituting for the assumed consumption growth rate process (8), it follows that

$$g_{i,t+1} = \delta_i + \phi_i x_t + \phi_i \eta_{t+1} + \epsilon_{i,t+1} - \epsilon_{i,t} \tag{19}$$

where x_t is the conditional expected aggregate consumption growth rate, and η_t is the innovation in aggregate consumption growth. Further, we assume that $\epsilon_{i,t+1} = \xi_i \epsilon_{i,t} + e_{i,t+1}$, and $\eta_{i,t}$ is independent of η_t. This assumption is equivalent to assuming that the stochastic cointegration parameter ϕ_i captures the exposure of $d_{i,t}$ to all consumption news. Note that if we considered the more general specification, where $e_{i,t+1} = \tau_i \eta_{t+1} + u_{i,t+1}$, the model's risk premia implications for all practical purposes are largely unchanged and coincide with assuming $\tau_i = 0$. Using cointegration to measure the exposure of dividends to consumption is particularly valuable when one considers the likelihood that both consumption and dividends are measured with stationary measurement error. Asymptotically, the presence of such measurement errors will not affect the estimates of the stochastic cointegration parameter (the consumption leverage parameter) ϕ_i.

We first solve for the log price-dividend ratio of an asset with a dividend stream as in equation (18). We show in the appendix that an asset's log price dividend ratio, $z_{i,t}$, is linear in the state variables:[5]

$$z_{i,t} = \bar{z}_i + A_{i,1}[x_t - \mu_x] + A_{i,2}\epsilon_{i,t} \tag{20}$$

$$r_{i,t+1} - E_t[r_{i,t+1}] = [\phi_i + \kappa_{i,1}A_{i,1}(\rho - \omega)]\eta_{t+1} + (1 + \kappa_{i,1}A_{i,2})u_{i,t+1} \tag{21}$$

where $\bar{z}_i$ is the mean of $z_{i,t}$, and

$$A_{i,1} = \frac{\phi_i - \frac{1}{\psi}}{1 - \kappa_{i,1}\rho}, \; A_{i,2} = \frac{\xi_i - 1}{1 - \kappa_{i,1}\xi_i} \tag{22}$$

The exposure of the ex-post return to the consumption shock is magnified by the term $A_{i,1}$—assets with large ϕ_i will have a larger degree of magnification, and consequently, the ex-post return will carry a larger compensation for consumption risk. The arithmetic risk premium on the asset will be determined by the risk premium expression (15), where the consumption β of the asset is

$$\beta_i = [\phi_i + \kappa_{i,1}A_{i,1}(\rho - \omega)] \tag{23}$$

The cointegration approach pursued above provides one economic model for dividends where it is assumed that c_t and $d_{i,t}$ are $I(1)$ and stochastically cointegrated. An alternative is to assume that $\xi_i = 1$, so that $d_{i,t}$ is not cointegrated with c_t even though both c and d are $I(1)$. In this case, the relationship between dividends and consumption can instead be modeled using a growth projection, and the key to deriving an asset's β is its exposure to the predictable variation in the expected consumption growth rate x_t. In this case, one can model the dividend growth rate, $g_{i,t}$, directly as

$$d_{i,t+1} - d_{i,t} = g_{i,t+1} = \delta_i + \varphi_i x_t + \eta_{i,t+1} \tag{24}$$

where φ_i, measures the covariance between dividend growth and *expected* consumption growth.[6] In this case, it follows that (see Appendix) the risk premium on any asset is

[5] The parameter $\kappa_{i,1}$ is an approximation constant that comes out of the Campbell-Shiller linearization of the log return and is typically very close to 1 (see Appendix).

[6] We can assume that the asset specific shock, $\eta_{i,t}$, is related to the aggregate consumption shock as follows, $\eta_{i,t} = \tau_i\eta_t + u_{i,t}$.

determined by equation (15), with

$$\beta_i = (\tau_i + A_{i,1}\kappa_{i,1}(\rho - \omega)) \tag{25}$$

The asset's risk is determined by its dividend growth exposure to expected consumption growth. Note that φ_i is an alternative way of measuring the aggregate consumption leverage of the dividend stream when $d_{i,t}$ and c_t are not stochastically cointegrated.

The asset's consumption beta, in conjunction with the restriction on the asset risk premium (see equation (15)), leads to sharp cross-sectional implications for risk premia. Typically these cross-sectional restrictions are tested by regressing the average return on an constant and the beta on the asset. Given the link between the consumption leverage and the beta of the asset—the same theoretical restrictions can be tested by a cross-sectional regression on consumption leverage. Assuming that $\kappa_{i,1}$ is identical across all assets (in the data, these differences are very small), it follows that the cross-sectional correlation between β_i and ϕ_i is one. This perfect correlation between ϕ_i and β_i implies that the cross-sectional regression of the average return on a constant and ϕ_i (i) provides the same predicted (i.e, theoretical) mean return as a cross-sectional regression of the average return on β_i, and (ii) the R^2 is the cross-sectional regression based on ϕ_i is equal to that from using β_i directly. Consequently, substituting the consumption beta (23) into the expression for the risk premium (15) leads to the following cross-sectional regression,

$$E[R_{i,t}] = \lambda_0 + \phi_i\lambda_c. \tag{26}$$

If the above cross-sectional regression used β_i instead of ϕ_i, then λ_0 would equal the mean risk-free rate and λ_c the risk-premium on the asset with unit consumption beta, that is $B_M\sigma_\eta^2$. When ϕ_i is used, then the estimated $\lambda_0 = E[R_f] - \frac{1}{\psi}q$, and $\lambda_c = (1+q)B_M\sigma_\eta^2$, with $q = \frac{\rho-\omega}{1-\kappa_1\rho}$. Our estimates of λ_0 and λ_c correspond to these quantities. Using the consumption leverage directly obviates the need to estimate additional preference and consumption growth rate parameters that go into the constriction of β_i–these, as stated above do not alter the predicted (theoretical) mean return for various assets. A similar result also obtains for the case in which the consumption leverage is estimated via the growth rate projection. Equation (26) will be used extensively to evaluate the empirical plausibility of the consumption leverage model.

3 Cash Flow Dynamics

3.1 Data

3.1.1 Aggregate Cash Flows and Factors

In our empirical tests, we consider the performance of the general equilibrium model of this paper, as well as alternative pricing models, in capturing cross-sectional variation in average returns. The models differ on the source(s) of priced risk. The first model, to which we refer as the *consumption leverage* model, is the equilibrium model developed in this paper. The priced risk in this model is aggregate consumption uncertainty. Following many past studies [e.g. Hansen and Singleton (1983)], we define aggregate consumption as seasonally adjusted real consumption of nondurables plus services. The aggregate consumption data are taken from the NIPA tables available from the Bureau of Economic Analysis.

The second set of models that we investigate are referred to as *unconditional factor* models. The particular models that we consider are the Consumption Capital Asset Pricing Model (C-CAPM), the Capital Asset Pricing Model (CAPM), the (human capital) CAPM with labor income (LCAPM), and a Three-Factor Model. The factor in the C-CAPM is the growth rate of consumption, defined as the first difference in log real aggregate consumption. The priced source of risk in the CAPM is a value-weighted index of stocks, obtained from CRSP. As in Jagannathan and Wang (1996), the LCAPM augments the standard CAPM with a return on labor income.[7] The three-factor Fama and French (1993) model posits that the priced risk factors are market, size, and value factors. The market risk premium is the excess return (over the return on a Treasury Bill with one month to maturity) on the value-weighted market return. The size factor is the difference in the return on a portfolio of small capitalization stocks and the return on a portfolio of large capitalization stocks. The value factor is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks.[8] Market capitalization and return data are taken from CRSP, and book values are formed from Compustat data.

[7] As in Lettau and Ludvigson (2001b), labor income is defined as real per capita wage and salary income plus transfer payments, less payments for social insurance, less taxes. Taxes are calculated by taking the ratio of wage and salary income to total income, and multiplying by personal taxes paid. The return on labor income is then computed as the difference in log real per capita labor income. These data are also obtained from the NIPA tables.

[8] For more detail on the formation of these factors, please see Fama and French (1993). Thanks to Kenneth French for making these data available.

The final set of models that we investigate mirror the unconditional models, but incorporate conditioning information. The conditioning variable, as in Lettau and Ludvigson (2001b), in these *conditional factor* models is the fitted residual, k_t, in the cointegrating relationship

$$c_t = b_0 + b_1 a_t + b_2 y_t + k_t$$

where c_t denotes log real aggregate consumption, a_t denotes log real aggregate wealth, and y_t denotes log real labor income. The consumption and labor series are defined as above; the wealth series is taken from the NIPA tables item "Household Net Worth." The resulting residual, k_t, is used as a conditioning variable in the models.[9] We estimate three conditional models: a conditional C-CAPM, a conditional CAPM, and a conditional LCAPM. These conditional models are formed by augmenting the factors in each model with the cross-product of the factors and the lagged k_t variable.[10]

3.1.2 Benchmark Portfolios

We focus on assets that are considered challenging and form the basis of empirical factors used to explain the cross-sectional risk premia on a wider set of assets. Indeed, the size, book-to-market, and the market return form the basis of the factor model in Fama and French (1993). Further, Carhart (1997), for example, has argued that this set of common factors should be augmented to include the momentum factor. Consequently, understanding the risk premia on these assets is an important step towards understanding the risk compensation of a wider array of assets. The data sets that we employ sort portfolios on the basis of various characteristics that generate dispersion in expected returns. We form portfolios on one-dimensional sorts on the basis of three characteristics. An additional advantage of pursuing this approach is that typically there are over 150 firms in each portfolio—this in addition to providing reasonably well diversified portfolios returns also helps in measuring the dividends in a reasonable manner by diversifying across the firm specific components in them.

[9] For further detail on the construction of this variable, please see Lettau and Ludvigson (2001a). Thanks to Martin Lettau for making these data available. Due to data constraints, the highest frequency with which k_t can be constructed is quarterly. Consequently, in our analysis of monthly data, we take the k_t realization as fixed throughout a given quarter.

[10] Menzly (2001) explores the ability of Lettau and Ludvigson (2001b)'s "scaled" models to explain the cross-sectional variation in average returns. Menzly both challenges the informational content of the k variable, and argues that influential data points are driving the model's apparent cross-sectional power.

Market Capitalization Portfolios

Banz (1981) finds that firms' market capitalization provides incremental power in explaining the cross-section of expected returns. Consequently, as in numerous past papers, [e.g. Campbell (1996)], we form a set of 10 portfolios on the basis of market capitalization. Firms are ranked on the basis of their market capitalization at the end of June of each year using NYSE capitalization breakpoints. CRSP returns and market value data are used to calculate value-weighted returns for these portfolios. As shown in Table 1, the data evidences a small size premium over the sample period. The mean real return on the lowest decile firms is 77 basis points per month, contrasted with a return of 69 basis points per month for the highest decile. The mean and standard deviations of these portfolios are similar in magnitude to those reported in previous work, such as Fama and French (1996).

Book-to-Market Portfolios

Our second data grouping is a set of ten portfolios sorted on the basis of the ratio of their book-to-market values. Fama and French (1992) find that the "book-to-market" ratio possesses incremental explanatory power for returns beyond CAPM β and market capitalization. Book value data is constructed from Compustat data.[11] The book-to-market ratio at year t is computed as the ratio of book value at fiscal year end $t-1$ to CRSP market value of equity at calendar year $t-1$. Firms are ranked on the basis of their book-to-market ratios at the end of June of each year using NYSE capitalization breakpoints, and value-weighted returns are calculated for these groups. This construction is the same as that in Fama and French (1993).

Sample statistics for these data are also presented in Table 1. The means of the portfolio returns are nearly monotonically increasing in book-to-market, consistent with the findings of Fama and French (1992). The highest book-to-market firms earn average real monthly returns of 100 basis points, whereas the lowest book-to-market firms average 65 basis points per month. These mean and standard deviations returns are similar to that found in the Fama-French data for our sample time period.

Momentum Portfolios

The third set of portfolios investigated are portfolios sorted on the basis of past returns. Jegadeesh and Titman (1993) sort NYSE and AMEX listed firms into decile portfolios on the

[11] As in FF, we define the book value as the Shareholders' Equity plus Balance Sheet Deferred Taxes and Investment Tax Credits, minus the value of Preferred Stock. Firms with nonpositive book values are deleted from the sample

basis of their returns over the past 3 to 12 months. The authors find that a "momentum" strategy that purchases the top decile and shorts the bottom decile of these firms earns a substantial profit after adjusting for CAPM beta. We sort firms into deciles based on their performance (i.e., cumulative return) over months $t-12$ through $t-1$ using CRSP. We then form value-weighted portfolios of these firms at time t. This approach of constructing the momentum portfolios is identical to Fama and French (1996).[12]

Summary statistics for the momentum portfolios are also presented in Table 1. As shown, this sort provides the highest dispersion in mean returns for the firm characteristics. The highest decile firms earn an average real return of 123 basis points per month, whereas the lowest decile firms lose 31 basis points per month on a real basis. This spread of 154 basis and the reported volatility of returns is comparable to Fama and French (1996). Additionally, consistent with Jegadeesh and Titman, we include only NYSE and AMEX firms.

3.1.3 Portfolio Dividends

To explore the long-run relationships between portfolio cash flows and consumption, we also need to extract dividend payments associated with these portfolios. In order to accurately characterize these dividend payments, consider the implications of a value-weight denoted by w_i, so that the portfolio total return is specified as follows:

$$\sum_i (w_i R_{i,t+1}) = \sum_i \{ \left[\frac{P_{i,t}}{\sum_i P_{i,t}} \right] (\frac{P_{i,t+1}}{P_{i,t}}) \} + \sum_i \{ \left[\frac{P_{i,t}}{\sum_i P_{i,t}} \right] (\frac{D_{i,t+1}}{P_{i,t}}) \}$$

where $P_{i,t}$ and $D_{i,t}$ are the market value and dividends of firm i, respectively. The above expression simplifies to

$$\sum_i (w_i R_{i,t+1}) = \left[\frac{\sum_i P_{i,t+1}}{\sum_i P_{i,t}} \right] + \left[\frac{\sum_i D_{i,t+1}}{\sum_i P_{i,t}} \right]$$

Hence, if $\sum_i P_{i,t}$ is the value of the investment today (the sum of all market values of firms in the portfolio), then the underlying aggregate dividend for the portfolio is the sum of dividends across all firms in the portfolio. Our focus on dividends is consistent with the economics of the model, where the consumption exposure of dividends is important for risk

[12] Jegadeesh and Titman find that skipping a month between the portfolio sorting and holding period accentuates the magnitude of the strategy profits.

premia. Campbell and Shiller (1988), along with others, also focus of dividends to address issues regarding asset prices.

As in Campbell and Shiller (1988), we proceed to compute dividends as follows. The total return for each firm i, $R_{i,t+1}$, is defined as:

$$R_{i,t+1} = \frac{P_{i,t+1} + D_{i,t+1}}{P_{i,t}} \tag{27}$$

$P_{i,t}$ is the equity price and $D_{i,t}$ represents the dividend payment, the firm's current dividend payment divided by its current price. For each firm i, we observe $R_{i,t+1}$, as well as the market value of outstanding equity, $P_{i,t}$, in CRSP. We extract dividends for a firm via the computation

$$D_{i,t+1} = P_{i,t}[R_{i,t+1} - \frac{P_{i,t+1}}{P_{i,t}}],$$

Since portfolios are value-weighted, this implies that the dividend payment for an entire portfolio over that period is just the sum of dividend payments across all firms in the portfolio. It is well known there are strong seasonals in this raw dividend series. As in Hodrick (1992), Heaton (1993), and Bollerslev and Hodrick (1995), we deseasonalize the raw dividend series by using a trailing 12-month moving average of the portfolio's aggregate dividends; the deseasonalized dividend series for a portfolio is $D_t = \frac{1}{12}\sum_{j=0}^{11}\sum_i D_{i,t-j}$.

Table 2 (Panel A) presents summary statistics on dividend growth rates for the 30 portfolios under consideration.[13] Dividend growth rates are quite variable for the momentum and value sorted portfolios. This is due to considerable turnover of firms in these portfolios. Firms paying dividends in one period in a particular portfolio may subsequently shift to another portfolio. For brevity, figure 1 displays real dividend levels for a somewhat coarser grid within the characteristic sorts. It is clear that the extreme portfolios in the momentum and

[13] We have calculated the fraction of firms that pay cash dividends in the different portfolios. We find that dividend payers generally represent in excess of 60% of the market value of the portfolios. For example, dividend payers make up 67 and 88 percent of the market value of the winner and high book-to-market portfolios, respectively. While the average number of firms in the portfolio paying dividends is some what lower, their value-weighted proportion, which is a better measure, is still quite high. This is particularly true for the momentum and book-to-market sorted portfolios. Since our portfolios are value-weighted, these proportions indicate that the dividend series that we construct are representative of the overall portfolio. Additionally, Campbell and Shiller (1998) show that changes in the level of share repurchases, a source for mismeasuring the observed dividend series is not as large once increased share issuance is accounted for. Finally, Jagannathan, Stevens, and Weisbach (2000) show that share repurchases are highly cyclical—this implies, that their inclusion should not alter our cointegration results which is all driven by the permanant componants in consumption and dividends.

value sorted portfolios exhibit negative correlation. This can be clearly seen in Panel B of Table 2, where correlations among the coarser portfolio dividend growth rates are provided. In the momentum and value cases, the correlations between the extreme growth rates are -0.70 and -0.13, respectively. This suggests that the characteristic sorts distinguish not only along the magnitude of mean returns, but also along cash flow dimensions—we discuss this further below. Finally, in Panel C of Table 2, we demonstrate summary statistics for the aggregate dividend growth rate, as well as the sum of all dividends within each portfolio sort. While the members across the portfolio sorts differ somewhat (for example some firms are excluded from the value portfolios because of Compustat data availability), it is clear that these sums generally match the characteristics of the aggregate CRSP dividend stream. For example, the resulting time-series from summing the dividends across the size portfolios is nearly identical to the aggregate dividend measure obtained directly from the value weighted market portfolio.

3.2 Measuring Consumption Exposure of Dividends

As discussed earlier we use stochastic cointegration to measure the consumption exposure of dividends. In particular, log dividends and consumption satisfy the following stochastic cointegrating relationship:

$$d_{i,t} = \mu_i + \delta_i \cdot (t) + \phi_i c_t + \epsilon_{i,t} \tag{28}$$

Following Engle and Granger (1987), we test the stochastic cointegration hypothesis by applying the augmented Dickey Fuller test on the residuals, $\epsilon_{i,t}$ (see Hamilton (1994), Chapter 19). We estimate the stochastic cointegration relationship using dynamic ordinary least squares (DOLS) as suggested by Stock and Watson (1993), that is we estimate;

$$d_{i,t} = \mu_i + \delta_i \cdot (t) + \phi_i c_t + \sum_{k=1}^{K} (\alpha_{-k} \Delta c_{t-k} + \alpha_k \Delta c_{t+k}) + \epsilon_{i,t} \tag{29}$$

where Δc_{t-k} denotes the first difference of log aggregate consumption, c_t, at the k^{th} lag; $\Delta \mathbf{c}_{t-k}$ denotes the vector of lags and $\Delta \mathbf{c}_{t+k}$ denotes the vector of leads. Standard OLS obtains when $\alpha_{-k} = \alpha_k = 0$. We select K so that we account for one year's worth of lags at any frequency considered; however, the estimates of the relevant consumption leverage parameter, ϕ_i, are not very sensitive to this choice. As discussed in Stock and Watson (1993) the inclusion of additional leads and lags removes the potential small-sample biases associated with standard OLS estimates.

Second, we explore the growth rate based specification, where $d_{i,t+1} - d_{i,t} = g_{i,t+1}$ as,

$$g_{i,t+1} = \delta_i + \varphi_i x_t + \eta_{i,t+1} \tag{30}$$

where φ_i measures, roughly speaking, the covariance between portfolio dividend growth and the expected consumption growth rate, x_t. Given x_t, this relationship is estimated by standard OLS.

To explore the growth rate based methodology, we first estimate an ARMA(1,1) process for the consumption growth rate. Our results show that both the AR and MA parameter estimates are highly significant at the monthly frequency. The autoregressive coefficient is 0.969 (S.E. 0.024) and the moving average coefficient is 0.920 (S.E. 0.034).[14] The autoregressive coefficient is fairly large, and exceeds the moving average coefficient, suggesting that shocks to consumption growth significantly affect agents' expectations of future consumption growth. Persistence in expected consumption growth rates is intimately related to the growth rate of the stochastic trend in consumption. Indeed, a stochastic trend can be identified from the estimated parameters of the ARIMA process (see Bansal and Lundblad (2000)). In Figure 2 (Panel A), the expected consumption growth rate, x_t (see equation (7)), implied by the estimated ARIMA parameters for the monthly frequency is plotted against the growth rate of the stochastic trend extracted from a standard two-sided Hodrick and Prescott (1997) (HP) filter. The HP filter is a frequently used alternative to decompose the level of a series into trend and cyclical components.[15] It is evident from the figure that the differences in the HP trend growth rate and the ARIMA-implied expected consumption growth rate are small. Further, there appears to be a cyclical nature to the two series, falling during observed recessions. This evidence suggests that there is a small component in consumption growth rates related to a stochastic trend in the level of consumption. Also, note that the predictable variation in the consumption growth rate is quite small; the R^2 in the ARMA(1,1) regression is only about 4%. However, as is evident from the size of ρ, the predictable variation component, x_t, in consumption is very persistent.

[14]The Andrews and Ploberger (1996) test of the hypothesis that $\rho = \omega$ is strongly rejected with a critical value of 15.51 (p-value 0.000). Estimates of the ARIMA(1,0,1) process using quarterly consumption data are comparable (for quarterly data), with estimates of ρ and ω equaling 0.788 (0.068) and 0.601 (0.099), respectively. For the quarterly data, the implied R^2 is about 9 percent, and the Andrews-Ploberger test is also soundly rejected with a p-value of 0.000.

[15]The HP trend is very extensively used in the real business cycle literature. See, for example, Kydland and Prescott (1982).

Portfolio Dividends and Consumption

We begin by exploring the nature of the relationships between relevant aggregate quantities. Namely, we consider the long-run relationship between aggregate consumption and aggregate dividends paid on all CRSP stocks. Table 3 reports the estimates of the cointegrating relationships between aggregate log consumption and aggregate log dividends, using the dynamic OLS procedure at the monthly frequency (the estimated coefficients are similar at lower frequencies). Aggregate dividends and consumption appear to share a long-run stochastic trend. To test whether the residual series from this estimation procedure is indeed stationary, we employ an augmented Dickey-Fuller test. While persistent, the null hypothesis that the residual series contain a unit root is rejected at the 5% level at adjusted critical values (Phillips and Ouliaris (1990)).[16] We conclude that aggregate dividends and consumption are stochastically cointegrated.

For the sorted 30 portfolios, Table 3 also presents estimated cointegration relationships at the monthly frequency (estimates at lower frequencies are similar). We estimate the long-run relationships between portfolio-specific dividends and aggregate consumption using the DOLS procedure described above. Robust standard errors are reported in parentheses, and as can be seen, many of the long-run relationships are estimated with precision. Generally speaking, the estimated ϕ_i's appear to increase as we move from low average return to high average return portfolios. For example, the long-run relationship between the extreme loser portfolio (M1) is estimated at -11.55 against aggregate consumption, whereas the long-run relationship between the extreme winner portfolio is estimated at 10.52. Similar relationships are observed among low and high book-to-market and market capitalization sorted portfolios, although the latter is much more muted in line with the less pronounced size premium. Since the cointegration specification facilitates a constant and a deterministic trend, the relationship described by ϕ_i reflects the degree to which portfolio dividends and consumption are stochastically cointegrated. We also consider similar cointegration measures using the raw (not deseasonalized) portfolio dividend series. The results are nearly identical, with the cross-sectional correlation between the two cointegration measures being almost 97%, hence the deseasonalization procedure is not important for our cointegration based evidence.

To test for cointegration, we conduct augmented Dickey-Fuller tests on the estimation residuals. Specifically, we test the hypothesis that the residuals from the cointegrating re-

[16]As developed in Phillips and Ouliaris (1990), adjusted critical values for standard unit root tests on the cointegration residual are appropriately adjusted for the error associated with the pre-estimation of the cointegration parameters.

lationship contain a unit root. Nearly all of the hypotheses are rejected at the 5% level. Given the overall evidence suggested by these tests, we conclude that the portfolio-specific dividends appear to share a common stochastic trend with aggregate consumption. Alternative growth rate based estimates of the projection coefficient φ_i (not shown) are highly correlated, $corr(\phi_i, \varphi_i) = 0.81$, with ϕ_i based on the cointegration regression.

4 Equity Risk Premia in the Cross-Section

In this section, we examine the relative performance of our consumption leverage model, standard unconditional factor models, and scaled conditional factor models in explaining the cross-section of equity risk premia. We perform standard cross-sectional regressions, utilizing the set of 31 portfolios detailed above (10 size, 10 momentum, 10 book-to-market, and the value-weighted market). Coefficients and standard errors are calculated via GMM in which all the risk exposures (the beta's) and cross-sectional risk prices are jointly estimated in one step (see Appendix for details).

4.1 Performance of Consumption Leverage Model

We begin our exploration by examining the ability of our consumption leverage model presented above to explain the cross-section of equity returns. Recall, the cross-sectional risk premia restriction is stated in equation (26), with the cross-sectional parameters of interest, given the consumption leverage, being λ_0 and λ_c.[17]

Tables 4 and 5 (Panel A) document the cross-sectional performance of the consumption leverage model at the monthly and annual frequencies. First, in both cases, the associated risk prices are positive and significant. Further, the adjusted R^2 is 48% (66%) at the monthly (annual) frequency, suggesting, as also exhibited in Figure 3, that the fundamental model can explain a considerable portion of the equity risk premia associated with this set of portfolios. In particular, the model is capable of explaining much of the variation across momentum returns, which we will see are particularly challenging for the alternative models considered. These results are particularly intriguing since the model's estimates of risk sensitivity are based solely upon the cash flows associated with a particular portfolio. That is, the high adjusted R^2's are associated only with measures of the relationship between portfolio cash

[17] Note that in the case where the consumption leverage is estimated via the co-integration approach, based on Engle and Granger (1987), we ignore the estimation error in estimating the superconsistent leverage parameters ϕ_i's.

flows and aggregate consumption. Estimates of the relationship between dividend growth and expected consumption growth, φ_i, yield similar cross-sectional patterns, and they can explain a comparable degree of the variation in average returns across our portfolios. Indeed, they explain, as reported in 4 (Panel A), about 70% of the cross-sectional variation in risk premia at the monthly frequency.

To provide an economic interpretation to these findings, we again employ the Hodrick Prescott (HP) filter to extract stochastic trends in each of the individual portfolio dividend series for comparison with the HP trend in consumption. This approach allows each portfolio dividend trend growth to be extracted free of information about aggregate consumption. In Figure 2, Panels B, C, and D display growth rates for the stochastic trend (first difference of the trend) for the six extreme decile portfolios in comparison to the consumption trend growth rate. For consumption, we again employ the growth rate of the HP-filtered stochastic trend also shown in panel A. Interestingly, several of the portfolio trend growth rates vary negatively with the consumption trend growth; see the extreme loser and low book-to-market portfolios, for example. Indeed, the negative stochastic cointegration coefficient estimate, ϕ_i, for the loser momentum portfolio reflects this observation. Most important, as suggested above, these portfolios are also those with generally lower average returns. Indeed, the correlation between the low book-to-market and loser momentum trend growth rates with the consumption trend growth rate are -0.23 and -0.51, respectively; in contrast, the correlation between the high book-to-market and winner momentum trend growth rates with the consumption trend growth rate are 0.53 and 0.54, respectively. These differences mirror those both in the cointegration parameter (consumption leverage) and in the risk premia. For example, the extreme loser and low book-to-market portfolios have negative exposures to the consumption stochastic trend movements, and hence low risk premia. In general, we observe that the cash flow trends appear to vary with the trend in consumption in concert with their average returns. Small shocks to the consumption trend growth (which as discussed earlier is close to the predictable variation in consumption growth rates) have large and differing implications, determined by the size and sign of consumption leverage, on different asset prices and risk premia. Assets with positive consumption leverage see their cash flows and asset valuations rise with the aggregate consumption (the economy) and hence carry a large positive risk premia.

One intriguing result from the regressions and indicated by the HP filter plots is the negative risk measure for high book-to-market portfolios. As shown in Figure 2, while the low book-to-market portfolio filtered cash flow displays a strong positive trend with consumption growth, the high book-to-market portfolio cash flow does not. This result is somewhat surprising in light of the interpretation of high book-to-market firms as those with high growth prospects. The results suggest that, although these firms may have strong growth prospects, these opportunities bear little relation to systematic risk. That is, the risk inherent in these growth opportunities does not covary strongly with the permanent component in consumption. As a result, this risk is not priced, which is reflected in the relatively low average returns.

As additional evidence, much of the value and momentum premia are duplicated by the growth rate based model, shown for example. These results are broadly similar across both the cointegration and growth rate based estimation methodologies, as well as data frequency. For the observed data, the value and momentum spreads are 35 and 154 basis points per month. Given the estimates of the consumption leverage and λ_c, their counterparts in the model are 34 and 112 basis points per month. Further, the size premium is close to zero both in the observed data and in the model. In this sense the estimated model can duplicate the size, momentum, and value premium spreads.

4.2 Performance of Unconditional Models

We continue our exploration by examining the ability of several standard unconditional (constant) β-representations to explain the cross-section of equity returns. Tables 4 and 5 (Panel A) document cross-sectional regressions, using our 31 portfolios, in the context of standard unconditional models at the monthly and annual frequency: the C-CAPM, the CAPM, Jagannathan and Wang (1996) labor income (human capital) model, and Fama and French (1993) three factor model. The tables report estimated risk prices, λ_k, associated with each risk source. Since the GMM estimation is performed in one step, standard errors (reported in the parentheses) reflect first stage time-series estimation of risk exposures. The tables also report cross-sectional R^2's, adjusted for degrees of freedom. To explore the ability of standard unconditional models to explain the cross-section of equity returns, the factors explored are g_t, the consumption growth rate, $R_{vw,t}$, the excess return on the CRSP value-weighted index, $R_{y,t}$, the return on labor income, $R_{SMB,t}$, the return on the size factor from Fama and French (1993), and $R_{HML,t}$, the return on the book-to-market factor from Fama and French (1993).

The first model we consider is the consumption based C-CAPM, for which the associated risk premia restriction is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{g,i}\lambda_g \tag{31}$$

where $\beta_{g,i}$ describes as asset's exposure to aggregate consumption risk; for all models, the betas are estimated using a standard time series regression of the portfolio return on the fundamental risk factors. At both the monthly and annual frequencies, the estimated price of consumption risk, λ_g, is not statistically significant. Indeed, at the monthly frequency, the estimated risk price is negative, clearly inconsistent with theory. However, the adjusted R^2 (for the annual frequency) for this regression is 18%, suggesting that this model explains some portion of the cross-sectional variation in average returns. For the monthly estimates, Figure 4 also demonstrates the inability of the unconditional C-CAPM to explain the portfolio returns.

We next consider the static CAPM, where risk is embodied entirely in the portfolio return's exposure to market risk. This model implies the following cross-sectional risk premia restriction:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw} \tag{32}$$

where $\beta_{vw,i}$ describes an asset's exposure to market risk, and λ_{vw} describes the price of market risk. In both cases, the estimates of λ_{vw} are not statistically significant. Further, the ability of the model to explain cross-sectional risk premia is limited at the monthly frequency, as demonstrated in the relatively low adjusted R^2. The general inability of the static CAPM to explain the cross-section of equity market returns is displayed graphically in Figure 4.

An alternative unconditional model which includes sensitivity to both aggregate market risk and labor income (human capital), posited by Jagannathan and Wang (1996), is considered next. The cross-sectional restriction implied by this specification is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw} + \beta_{y,i}\lambda_y \tag{33}$$

where λ_y reflects the risk price associated with labor income growth. At the annual frequency, the addition of this second risk factor adds little at the monthly frequency. Further, while the adjusted R^2 is 39% at the annual frequency, it is much smaller at the monthly, suggesting a great deal of the cross-sectional variation in risk premia is still left unexplained. This can also be seen clearly in Figure 4, where pricing errors are quite large.

Finally, we present results for the Fama and French three-factor model. The cross-sectional risk premia restriction implied by the formulation is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw} + \beta_{SMB,i}\lambda_{SMB} + \beta_{HML,i}\lambda_{HML} \tag{34}$$

While the cross-sectional R^2 is 17% at the monthly frequency, the ability of the model to explain the cross-section of equity returns in our menu is quite poor at the annual frequency. In particular, while the model does quite well in explaining the risk premia associated only with 10 size plus the 10 value-sorted portfolios (The R^2 at the monthly frequency is 63% if we foscus only on these 20 portfolios), the addition of momentum portfolios is particularly challenging for their three factor model. Fama and French (1996) also demonstrate that the model cannot explain momentum portfolio returns. (see also Figure 4)

4.3 Performance of Conditional (Scaled) Models

Despite the difficulty the simple constant-β models have in explaining the cross-section of risk premia for our challenging assets menu, there is evidence that conditional (scaled) factor models, which essentially facilitate time-varying risk exposures, are capable of describing the cross-section of equity returns (see Ferson and Harvey (1991), Jagannathan and Wang (1996), and Lettau and Ludvigson (2001b), for example). We augment the C-CAPM, CAPM and labor income models with a single scaling variable, k_t.

We explore the effects of including scaled factors in explaining the cross-section of risk premia. As before, the factors are g_t, the growth rate of aggregate consumption, $R_{vw,t}$, the return on the CRSP value-weighted index, and $R_{y,t}$, the return on labor income. In addition we multiply these primitive factors by k_{t-1} to create additional scaled factors.[18] Tables 4 and 5 (Panel B) document cross-sectional R^2's associated with these specifications.

We first consider a conditional (scaled) version of the C-CAPM, for which the risk premia restriction associated with this model is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{g,i}\lambda_g + \beta_{gk,i}\lambda_{gk} \tag{35}$$

At both the monthly and annual frequencies, the cross-sectional R^2's suggests that the conditional C-CAPM can explain about 15% of the variation in cross-sectional risk premia.

[18]The k data are obtained from Lettau's web page; the k observation used in determining risk measures for the monthly frequency remains constant throughout a given calendar quarter. At the annual frequency, we utilize the c, a, and y data available on Lettau's webpage to estimate cointegrating parameters for the consumption-wealth relationship, and retrieve k.

Relative to the performance of the unconditional C-CAPM, the addition of the k conditioning argument appears to be important in explaining expected returns for this broader menu of asset (at least at the monthly frequency). However, the sign and significance of the estimated risk prices vary over the specifications and frequencies making economic interpretation somewhat difficult.

Next, we consider a conditional (scaled) version of the standard CAPM, for which the cross-sectional risk premia restriction is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{k,i}\lambda_k + \beta_{vw,i}\lambda_{vw} + \beta_{vwk,i}\lambda_{vwk} \tag{36}$$

The improvement in terms of the ability of the model to explain cross-sectional variation in risk premia over the unconditional CAPM is apparent in terms of the adjusted R^2 (again, at least at the monthly frequency). At the monthly frequency, the "scaled" model can explain about 11% of the cross-sectional variation in risk premia, which is an improvement over the static CAPM. Also, the signs and significance of the risk prices vary across specifications. Nevertheless, this suggests that a conditional version of the CAPM can only capture a small portion of the dispersion in observed risk premia (see Figure 5).

Finally, we consider a scaled version of the two-factor labor income (human capital) model, for which the cross-sectional risk premia restriction is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{k,i}\lambda_k + \beta_{vw,i}\lambda_{vw} + \beta_{R_y,i}\lambda_y + \beta_{vwk,i}\lambda_{vwk} + \beta_{R_yk,i}\lambda_{yk} \tag{37}$$

At both the monthly and annual frequency, the model appears to explain some of cross-sectional variation in returns, where the adjusted R^2 is over 35% at the annual frequency (see Figure 5).

In sum, scaled conditional factor models (the C-CAPM, CAPM, and labor income) generally perform better than their unconditional counterparts, particularly at the monthly frequency, when forced to confront this collection of asset returns. However, the signs and significance of the estimated risk prices are extremely sensitive to the precise specification employed, thus making economic interpretation is somewhat difficult. In sharp contrast, the cross-sectional implications of the consumption leverage model are consistent across the frequency considered. The scaled models capture the intuition that in addition to average beta risk, unconditionally, the covariation between the conditional beta of the asset and the aggregate risk premium also influences the risk premium. Our consumption leverage model has constant consumption beta's, and hence does not rely on the second channel to explain risk premia. The time-varying beta models typically do not provide the equilibrium mapping between the variables that lead to variation in the asset's beta and it underlying cash flows.

It is worth noting that standard consumption based models, unconditional or conditional, obtain the asset's beta by projecting returns on the ex-post consumption growth in the time-series. As is well recognized, and reinforced above, this approach has considerable difficulties in explaining risk premia in the cross-section. In contrast, our consumption leverage model does quite well in capturing risk premia. If there are considerable measurement errors or other difficulties in measuring the appropriate level of consumption (see Campbell (1996)), then indeed the usual consumption beta may be a poor estimate of the true consumption beta that is needed to explain risk premia. The consumption leverage model, based on the cointegration approach which utilizes the levels of consumption and dividends, is fairly robust to stationary measurement errors in consumption and dividends as these should not alter the cointegration relationship. Even the growth rate approach which extracts a smooth exponential trend (see equation 7), due to the exponential smoothing, may mitigate the contaminating effects of mis-measuring consumption. This indeed seems to be the case as the correlation between the two measures of consumption leverege across assets is in excess of 80%.

In Table 6, we report results which give a sense of the relative merits of the different factors in explaining the cross-section of risk premia. In particular, we augment the consumption leverage model to include additional factors and inquire if the consumption leverage continues to be important in their presence. First, note that the risk premium on consumption in highly significant and positive in all cases. With the inclusion of the consumption leverage, none of the size, book-to-market, or market factors are significant. Further, the cross-product terms between consumption growth, labor income growth, or the market returns and the lagged consumption wealth ratio are not statistically significant as well. Finally, the overall adjusted R^2's are not considerably larger than the growth rate based consumption leverage model at the monthly frequency. Hence, the risk-premia implications based on our consumption leverage model seem very robust to the inclusion of additional risk factors.

5 Robustness Checks

5.1 Alternative asset menus

In our investigation, we have focused on portfolios sorted on the basis of past return, market capitalization, and book-to-market ratio. However, there are many alternative selections of portfolios that could be considered. To evaluate the robustness of our results we augment the asset menu with an additional 10 portfolios sorted on the basis of industry. We find that the consumption leverage model explains 44% of the cross-sectional variation in returns. Moreover, the risk premium, λ_c continues to be positive and significant (estimate=0.026, standard error=0.005). For this asset menu, the consumption CAPM explains 12% of the cross-sectional variation in average return, the market based CAPM explains 8% of this variation, and the three-factor model explains 0.1%. These results indicate that the consumption leverage model continues to perform much better than the alternative models when the industry portfolios are included in the asset set.

An alternative selection of 25 portfolios is the bi-variate sort along size- and book-to market dimensions used in Fama and French (1993). Although this selection produces high dispersion in mean returns, it ignores the important dimensions of momentum and industry. Further, the bi-variate sort in some cases yields very few firms, as few as 20 in some of the portfolios. This issue is problematic in terms of analyzing risk-premia of reasonably diversified portfolios, and is even more problematic in determining the dividends (or earnings) associated with the portfolio. The relevant cash-flow information for the portfolio in this case loses the benefits of cross-sectional diversification, which mitigates the effects of fairly volatile firm specific components in cash-flows. Because of this issue, in addition to the fact that our single dimensional portfolio sorts form the basis for key empirical factors designed to explain risk-premia on a wider range of assets, we focus on one-dimensional portfolio sorts. Our view is consistent with Cochrane (2000), who argues that empirical work on the cross-section of assets should focus on important cross-sectional dimensions, which may be well characterized by single dimensional sorts.

5.2 Measures of Payoffs

We have chosen to focus on dividends as a measure of payouts, the present value of which determines asset prices. We recognize that payoffs could also include payment by firms to shareholders in forms other than cash dividends. Despite this issue, we think dividends measure the exposure of payouts to the permanent component of consumption quite well. That is, we believe that the objects that we wish to measure, the long-run component in payouts and its exposure to the permanent component in consumption, are not contaminated by our use of dividends. Stated differently, payouts and dividends are co-integrated with a cointegation parameter of one. The issue of the differences between payouts and dividends in perhaps most relevant from the late 1980's due to increased volume in repurchases. However, at an aggregate level, ?) show that the use of share repurchases is highly procyclical. Since our focus is on the permanent component in consumption, repurchases are unlikely to affect the co-integration results that we report. Further Ziv ** (fortcoming JOF) argue that dividends provide information regarding corporate profits and earnings. This finding indicates that dividends contain valuable economic information. Deriving a clean measure of payouts at an firm level is typically not feasible; as pointed out by Campbell and Shiller, many firms in the 90's issue below market price stock options.

To ensure the robustness of our results, we also report the evidence based on the use of earnings to measure payouts instead of dividends. Earnings are computed for each portfolio from Compustat. The consumption leverage model continues to perform reasonably well when dividends are replaced with earnings. The market price of consumption risk is still significant and positive, and the model explains about 36% of the cross-sectional variation in mean asset returns. The difference in results between the earnings and dividends is due to the fact that earnings include physical investment by firms; the inclusion of investments which have a different exposure to the permanent components in aggregate consumption and hence distorts the exposure relative to payouts. We have also tested (not reported) the cointegration relation between portfolio dividends and earnings. While we find that these series are cointegrated for almost all of the portfolios that we investigate, the cointegration parameter is not equal to one. Hence, the permanent component exposure of the two series to consumption is different. In all, it seems that the long run permanent components of payouts are reasonably measured by dividends, our ability to explain the cross-sectional differences in the observed risk-premia, indicates this.

5.3 Long Horizon Results, 1926-1999

Since co-integration captures co-movements in long-run or permanent components of cash flows and consumption, we consider a longer sample period as an additional robustness check. We repeat the cross-sectional analysis using a set of 21 portfolios, sorted on the basis of past return and market capitalization, augmented by the value-weighted index.[19] These portfolios are constructed using CRSP data and are sampled at an annual frequency over the period 1926-1999. Table 7 presents summary statistics for these data in Panel A. As shown in the table, these data exhibit a strong momentum premium (13.68%), as well as a large size premium (5.77%). These premia are also reflected in the consumption leverage risk measures displayed in the table.

Table 7 indicates that the consumption leverage model performs quite well. The adjusted R^2 for the model over the sample period is 0.69, and the consumption risk premium is large and precisely measured (Coefficient=0.534, Standard Error=0.081). In contrast, the alternative unconditional models do not fare as well in capturing cross-sectional variation in returns. The consumption CAPM performs the best of the three unconditional models analyzed, with an adjusted R^2 of 0.169. The market-based CAPM and three-factor model do not perform as well; the CAPM explains a limited amount of the variation in returns across these portfolios ($\bar{R}^2 = 0.059$), and the three-factor model also explains a relatively small portion of return variability ($\bar{R}^2 = 0.120$).

These results confirm the results in Table 5 and suggest the strength of the consumption leverage model in capturing cross-sectional variation in mean returns. The results suggest that the findings are robust to the use of a longer sample, which is particularly important in light of the co-integration technology. Further, the results indicate that the model captures the size premium when it is present in the data; over the longer sample the size premium is more pronounced and reflected in the consumption leverage risk measures.

6 Conclusion

The idea that differences in exposures to sources of systematic risk should justify differences in risk premia across assets is fundamental to financial economics. We present a simple, parsimonious general equilibrium model, in which consumption betas are directly linked to the consumption leverage of dividends. We show that this consumption based model with constant consumption beta's does very well in terms of explaining the cross-sectional differences in the risk premia on 31 portfolios comprised of 10 size, 10 momentum, and 10 book-to-market portfolios, in addition to the value-weighted market portfolio. We measure the consumption leverage of a given dividend stream either by relying on the stochastic

[19]Since the Compustat data are not available prior to the 1950s, we omit the book-to-market sort.

cointegration between dividends and consumption or, as an alternative approach, by the projection coefficient of ex-post dividend growth on the expected consumption growth rate.

Our consumption leverage model can account for about 65% of the cross-sectional differences in the risk premia across the 31 assets, and the risk premium associated with the consumption risks is positive and highly significant. This performance compares very favorably against standard factor and time-varying beta models which account for about 20-30% of the cross-sectional variation in risk premia. The Fama-French three factor model can justify about 20% of the cross-sectional differences in the risk premia. Our evidence suggests that there is a small predictable, and very persistent, component in consumption. Small shocks to this component have very long lasting effects for future expected growth rates, and hence these shocks have a large impact on asset prices. Dividends of different assets have varying exposures to this aggregate source of non-diversifiable risk requiring different risk compensation. We show that the extreme loser and low book-to-market portfolio dividends have negative consumption leverage and low risk premia. In sharp contrast, the winner portfolio and the high book-to-market portfolio have large positive consumption leverage and large positive risk premia. We show that our specification can duplicate much of the value spread (high book-to-market less low book-to-market), the momentum spread (winner firm less looser firms), and the close to zero size spread (small firm less large firm return)

Bansal and Yaron (2000) show that a similar economic model can also justify the observed market risk premia, the low risk free rate, market volatility, and key aspects of predictable variation in returns and return volatility. This evidence, along with the strong support we find for the related consumption leverage model in justifying the cross-section of risk premia, suggests that risks contained in cash flow growth rates are important in interpreting the behavior of financial markets.

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7 Appendix

We have defined preferences (Epstein-Zin) and consumption/aggregate cash flow dynamics (ARIMA) for the economy. An equilibrium will then be a price function that, given preferences and consumption dynamics, will clear the market. In order to move to this equilibrium, we begin by noting that, by definition, the return on any asset is given by

$$R_{i,t+1} = \frac{1 + \frac{P_{i,t+1}}{D_{i,t+1}}}{\frac{P_{i,t}}{D_{i,t}}} \frac{D_{i,t+1}}{D_{i,t}} \tag{38}$$

Let $G_{i,t+1} = \frac{D_{i,t+1}}{D_{i,t}}$ and $Z_{i,t} = \frac{P_{i,t}}{D_{i,t}}$. Campbell and Shiller (1988a) derive a Taylor series approximation to (38), which is expressed in log form as

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} z_{i,t+1} - z_{i,t} + g_{t+1} \tag{39}$$

where lowercase letters represent logs of their uppercase counterparts.[20] Thus, the return on any asset at time $t+1$ is a function of its price-dividend ratio at times t and $t+1$, and the growth rate in its cash flows.

7.1 Equilibrium

We make two assumptions in order to solve for the wealth consumption portfolio as functions of the expected consumption growth. First, we conjecture that the log wealth consumption ratio, $z_{c,t}$, is linear in the state variable, x_t:

$$z_{c,t} = A_{c,0} + A_{c,1} x_t \tag{41}$$

Our second assumption is that the return on the portfolio that pay consumption and the IMRS are joint lognormally distributed. We then observe that, as shown in Bansal and Yaron (2000), we can solve for the coefficient $A_{c,1}$ and $A_{i,2}$ using the relationship

$$E_t \left[\exp(m_{t+1} + r_{c,t+1}) \right] = 1$$

[20] $\kappa_{i,0}$ and $\kappa_{i,1}$ are constants from the Taylor series approximation:

$$\kappa_{i,1} = \frac{\exp(\bar{z}_i)}{1 + exp(\bar{z}_i)}, \ \kappa_{i,0} = -\log(\kappa_{i,1}) - (1 - \kappa_{i,1}) \bar{z}_i \tag{40}$$

and the fact that, for a normally distributed random variable X,

$$E\left[e^X\right] = e^{E[X]+\frac{1}{2}Var[X]}$$

Aggregate consumption growth follows an ARMA(1,0,1) process as follows:

$$\begin{aligned} c_{t+1} - c_t &= g_t = (1-\rho)\mu_c + \rho g_t + \eta_{t+1} - \omega\eta_t & (42) \\ x_{t+1} &= (1-\rho)\mu_x + \rho x_t + (\rho-\omega)\eta_{t+1} & (43) \end{aligned}$$

where x_t is the expected consumption growth rate. Using the Epstein-Zin equilibrium pricing restriction and the approximated definition of return:

$$\begin{gathered} \theta \ln \delta - \tfrac{\theta}{\psi}((1-\rho)\mu_c + x_t + x_t) \\ +(\theta)[\kappa_{c,0} + \kappa_{c,1}\{A_{c,0} + A_{c,1}((1-\rho)\mu_x + \rho x_t)\} - A_{c,0} - A_{c,1}x_t + (1-\rho)\mu_c + x_t] \end{gathered} \quad (44)$$

Isolate the terms related to the expected consumption growth, x_t,

$$-\frac{\theta}{\psi} + (\theta)[\kappa_{c,1}A_{c,1}\rho - A_{c,1} + 1] = 0 \quad (45)$$

By solving for the coefficients, the solution for the log wealth consumption ratio is given by

$$A_{c,1} = \frac{1-\frac{1}{\psi}}{1-\kappa_{c,1}\rho} \quad (46)$$

This implies the following for the innovations to the wealth portfolio return:

$$r_{c,t+1} - E_t[r_{c,t+1}] = \eta_{c,t+1} = B_c\eta_{t+1} \quad (47)$$

where $B_c = 1 + \kappa_{c,1}(\rho-\omega)A_{c,1}$.

Given the solution for the log wealth consumption ratio, the pricing kernel innovation can be rewritten solely as a function of the consumption growth rate innovation:

$$\eta_{M,t+1} = -\frac{\theta}{\psi}\eta_{t+1} - (1-\theta)\eta_{c,t+1} = -[-\frac{\theta}{\psi} - (1-\theta)B_c]\eta_{t+1} \equiv B_M\eta_{t+1} \quad (48)$$

where $B_M = -[-\frac{\theta}{\psi} - (1-\theta)B_c]$. The geometric risk premium on any asset is given by

$$E_t\left[r_{i,t+1} - r_{f,t}\right] = cov_t\left(-\eta_{M,t+1}, r_{i,t+1}\right) - var(r_{i,t+1})/2 \tag{49}$$

Substituting the form of the solution coefficients, and converting to the arithmetic risk premium yields

$$E_t\left[R_{i,t+1} - R_{f,t}\right] = \beta_i[B_M\sigma_\eta^2] \tag{50}$$

where the fundamental $\beta_i = \frac{cov(r_i,\eta)}{\sigma_\eta^2}$.

7.2 Consumption Leverage Model

To solve for individual equilibrium asset prices, we conjecture that $z_{i,t}$ is linear in the state variables, x_t and $\epsilon_{i,t}$:

$$z_{i,t} = A_{i,0} + A_{i,1}x_t + A_{i,2}\epsilon_{i,t} \tag{51}$$

As with the log wealth consumption ratio, we can solve for the coefficients $A_{i,1}$ and $A_{i,2}$. Asset dividend and aggregate consumption are stochastically cointegrated as follows:

$$d_{i,t+1} = \mu_i + \delta_i \cdot (t+1) + \phi_i c_{t+1} + \epsilon_{i,t+1} \tag{52}$$

Using the solution for the log wealth consumption ratio and the approximated definition of the return, we isolate the terms in the Epstein-Zin first order condition $E_t\left[\exp(m_{t+1} + r_{i,t+1})\right] = 1$ related to the expected consumption growth, x_t,

$$-\frac{1}{\psi} + \phi_i - A_{i,1}[1 - \kappa_{i,1}\rho] = 0 \tag{53}$$

Second, isolate the terms related to the asset specific cyclical component, $\epsilon_{i,t}$,

$$\kappa_{i,1}A_{i,2}\xi_i - A_{i,2} + \xi_i - 1 = 0 \tag{54}$$

By solving for the coefficients, the solution for the log price dividend ratio is given by

$$A_{i,1} = \frac{\phi_i - \frac{1}{\psi}}{1 - \kappa_{i,1}\rho} \; A_{i,2} = \frac{\xi_i - 1}{1 - \kappa_{i,1}\xi_i} \tag{55}$$

From the equilibrium solution, the geometric risk premium on any asset is given by

$$E_t\left[R_{i,t+1} - R_{f,t}\right] = \beta_i[B_M \sigma_\eta^2] \tag{56}$$

Substituting the solution for z_i in to the expression for the ex-post return implies that the return innovation is

$$r_{i,t+1} - E_t[r_{i,t+1}] = [\phi_i + \kappa_{i,1} A_{i,1}(\rho - \omega)]\eta_{t+1} + (1 + \kappa_{i,1} A_{i,2}) u_{i,t+1} \tag{57}$$

The asset's beta is, $\beta_i = \frac{cov_t(r_{i,t+1}, \eta_{t+1})}{\sigma^2_{\eta_{t+1}}}$, given the return innovation it follows that $\beta_i = \phi_i + \kappa_{i,1} A_{i,1}(\rho - \omega)$.

7.3 Alternative Dividend Growth Rate Specification

As an alternative, we directly specify the dynamics for asset-specific real log cash flow growth, $g_{i,t}$, in relation to the expected growth rate of consumption, x_t:

$$d_{i,t+1} - d_{i,t} = g_{i,t+1} = \delta_i + \varphi_i x_t + \eta_{i,t+1} \tag{58}$$

Given this specification, we conjecture that $z_{i,t}$ is linear in the state variable, x_t:

$$z_{i,t} = A_{i,0} + A_{i,1} x_t \tag{59}$$

Again, using the solution for the log wealth consumption ratio and the approximated definition of the return, we isolate the terms in the Epstein-Zin first order condition $E_t\left[\exp(m_{t+1} + r_{i,t+1})\right] = 1$ related to the expected consumption growth, x_t:

$$-\frac{1}{\psi} + \varphi_i - A_{i,1}[1 - \kappa_{i,1}\rho] = 0 \tag{60}$$

The solution for the coefficient is given by

$$A_{i,1} = \frac{\varphi_i - \frac{1}{\psi}}{1 - \kappa_{i,1}\rho} \tag{61}$$

As above, the arithmetic risk premium on any asset is given by

$$E_t\left[R_{i,t+1} - R_{f,t}\right] = \beta_i[B_M \sigma_\eta^2] \tag{62}$$

Since the return innovation is

$$r_{i,t+1} - E_t[r_{i,t+1}] = [\tau_i + \kappa_{i,1} A_{i,1}(\rho - \omega)]\eta_{t+1} + \eta_{i,t+1}, \tag{63}$$

it follows that the consumption beta of the asset, $\beta_i = \tau_i + \kappa_{i,1} A_{i,1}(\rho - \omega)$.

7.4 GMM Estimation

Let the true parameter vector be given by:

$$\Psi_0 = \begin{bmatrix} \alpha_1 & \cdots & \alpha_N & \beta_1' & \cdots & \beta_N' & \lambda_0 & \lambda' \end{bmatrix} \tag{64}$$

where the β_i and λ vectors are determined by the model specification. Let $R_{i,t}$ denote the return on the ith portfolio. There are N portfolios in total. The basic regression that we run for each portfolio's return is

$$R_{i,t+1} - R_{f,t} = \alpha_i + \beta_i' \mathbf{f}_{t+1} + e_{i,t+1} \tag{65}$$

for a vector of K risk factors, $\mathbf{f}_{t+1}$, determined by each model. $f_{k,t}$ represents the realization of factor k at time t, and β_k indicates the sensitivity associated with risk factor k. $e_{i,t}$ is assumed to be conditionally mean independent of the risk factors $f_{k,t}$. We formulate the following moment conditions to estimate the risk sensitivities (β_i's):

$$\begin{aligned} E[e_{i,t+1}] &= 0 \ \forall i = 1, \ldots, N \\ E[e_{i,t+1}\mathbf{f}_{t+1}] &= 0 \ \forall i = 1, \ldots, N \end{aligned} \tag{66}$$

The $\beta_i' s$ are identified in the time series. We also identify the risk prices in the cross-section by exploiting the following set of moment conditions:

$$E[R_{i,t+1} - \lambda_0 - \beta_i' \lambda] = 0 \ \forall i = 1, \ldots, N \tag{67}$$

We can stack the sample counterparts to the moment conditions (66) and (67) as follows (Hansen (1982)):

$$g_T(\Psi) = \frac{1}{T} \sum_{t=1}^{T} f(X_t, \Psi) \tag{68}$$

This yields $[N + N \cdot K + (K+1)]$ parameters to be estimated with $[N + N \cdot K + N]$ moment conditions, where $N > K + 1$. We construct an exactly identified system by setting linear combinations of g_T, an $[N(K+1) + N] \times 1$ vector, equal to zero. Specifically, we write the moment conditions as

$$A'_T g_T = 0 \tag{69}$$

Our choice of A_T, an $[N(K+1) + N] \times [N(K+1) + (K+1)]$ matrix, is designed to ensure that the estimates are consistent with OLS.

$$A_T = \begin{bmatrix} I_{N(K+1)} & 0_{N(K+1)\times 1} & 0_{N(K+1)\times 1} & \cdots & 0_{N(K+1)\times 1} \\ 0_{N,N} & 1_{N\times 1} & \hat{\beta}_1 & \cdots & \hat{\beta}_K \end{bmatrix} \tag{70}$$

where $I_{N(K+1)}$ is the identity matrix, $0_{N(K+1)\times 1}$ and $1_{N(K+1)\times 1}$ denote column vectors of zeros and ones, respectively, and $\hat{\beta}_k$ is an $N \times 1$ vector of the estimated sensitivities to risk factor k. We then estimate the parameters, Ψ_T, of the exactly identified system to ensure that $A'_T g_T(\Psi_T) = 0$. Based on Hansen (1982), we know that

$$\sqrt{T}(\Psi_T - \Psi_0) \sim N(0, (AD)^{-1}(ASA')(AD)^{-1\prime}) \tag{71}$$

where D is the gradient of the stacked moment conditions in equation (68), and S is the variance-covariance matrix of the moment conditions, for which the sample counterpart is estimated using Newey and West (1987) with 12 lags.

Table 1: **Summary Statistics**

Panel A: 30 Portfolios

Portfolio	Mean	Std. Dev.	Portfolio	Mean	Std. Dev.
M1	-0.0031	0.0762	S6	0.0076	0.0528
M2	0.0023	0.0596	S7	0.0073	0.0521
M3	0.0037	0.0543	S8	0.0073	0.0502
M4	0.0057	0.0488	S9	0.0069	0.0474
M5	0.0048	0.0467	S10	0.0069	0.0428
M6	0.0055	0.0462	B1	0.0065	0.0517
M7	0.0068	0.0471	B2	0.0076	0.0493
M8	0.0081	0.0478	B3	0.0067	0.0498
M9	0.0100	0.0521	B4	0.0063	0.0503
M10	0.0123	0.0624	B5	0.0066	0.0459
S1	0.0077	0.0629	B6	0.0081	0.0466
S2	0.0078	0.0602	B7	0.0079	0.0451
S3	0.0076	0.0586	B8	0.0079	0.0442
S4	0.0085	0.0573	B9	0.0081	0.0451
S5	0.0079	0.0549	B10	0.0100	0.0499

Panel B: Aggregate Growth Rates

	Mean	Std. Dev.
VW Index	0.0069	0.0456
Consumption	0.0026	0.0037
Labor Income	0.0013	0.0081

Table 1 presents descriptive statistics for the 30 characteristic sorted portfolios and the aggregate variables used in estimation. The portfolios examined are portfolios formed on momentum (M1-M10), market capitalization (S1-S10), and book-to-market ratio (B1-B10). The momentum portfolio returns at time $t+1$ are formed by sorting NYSE and AMEX firms into deciles on the basis of their returns over the period $t-12$ through $t-1$ and value-weighting the returns on these firms within each decile. Capitalization portfolios are formed by sorting NYSE, AMEX, and NASDAQ firms by their market capitalization as of June of each year, and holding the capitalization decile constant for one year. Returns are value-weighted and NYSE breakpoints are used in calculating a firm's decile. Book-to-market portfolios are formed by sorting NYSE, AMEX, and NASDAQ firms based on their market capitalization as of June of each year divided by their book value as of the most recent fiscal year end available. Returns are value-weighted. The VW Market represents the return on a value-weighted portfolio of all NYSE, AMEX, and NASDAQ listed stocks. Consumption is the aggregate per capita consumption of nondurables and services. Labor income is aggregate per capita income less dividend income. Data are converted to real using the CPI. The data cover the period 7/1966 through 12/1999, for a total of 402 monthly observations.

Table 2: **Descriptive Statistics: Cash Flow Growth Rates**

Panel A: Mean and Volatility of Growth Rates

Portfolio	Mean	Std. Dev.	Portfolio	Mean	Std. Dev.
M1	-0.0029	0.1191	S6	0.0025	0.0199
M2	-0.0032	0.0955	S7	0.0024	0.0198
M3	-0.0004	0.0802	S8	0.0018	0.0249
M4	0.0005	0.0649	S9	0.0020	0.0212
M5	0.0018	0.0577	S10	0.0028	0.0170
M6	0.0037	0.0528	B1	0.0040	0.0398
M7	0.0041	0.0550	B2	0.0029	0.0500
M8	0.0049	0.0721	B3	0.0024	0.0505
M9	0.0068	0.0885	B4	0.0010	0.0650
M10	0.0076	0.1161	B5	0.0017	0.0677
S1	0.0032	0.0238	B6	0.0033	0.0623
S2	0.0039	0.0207	B7	0.0036	0.0683
S3	0.0037	0.0183	B8	0.0059	0.0694
S4	0.0035	0.0228	B9	0.0073	0.0609
S5	0.0029	0.0218	B10	0.0085	0.0586

Panel B: Growth Rate Correlations

Momentum				Size				Book-to-Market			
	M1-M4	M5-M6	M7-M10		S1-S4	S5-S6	S7-S10		B1-B4	B5-B6	B7-B10
M1-M4	1.00	0.16	-0.70	S1-S4	1.00	0.28	0.18	B1-B4	1.00	-0.11	-0.13
M5-M6		1.00	-0.07	S5-S6		1.00	0.23	B5-B6		1.00	-0.33
M7-M10			1.00	S7-S10			1.00	B7-B10			1.00

Panel C: Measures of Aggregate Dividend Growth

Portfolio	Mean	Std. Dev.	Correlation with Aggregate
Aggregate	0.0019	0.0106	—
M1-10	0.0018	0.0108	0.955
S1-10	0.0019	0.0106	0.999
B1-10	0.0028	0.0138	0.830

Table 2 presents descriptive statistics for the real cash flow growth rates of the portfolios utilized in this study. In Panel A, we present means and standard deviations of the growth rate in smoothed portfolio dividends over the period 1/1967 through 12/1999. In Panel B, we depict correlations within characteristic sorts for coarser portfolio partitions. M1-M4 represents the dividend growth rate associated with the first through fourth momentum decile, M5-M6 represents the fifth through sixth decile, and M7-M10 represents the seventh through tenth decile. Labels for the size and book-to-market sorted portfolios are interpreted similarly. M1-10 represents the sum of dividends across all momentum portfolios (same for size and value portfolios). Finally, Aggregate refers to the growth rate in the sum of dividends across all CRSP firms.

Table 3: **Stochastic Cointegration**

Portfolio	Cointegration	ADF	Portfolio	Cointegration	ADF
M1	-11.546 (3.074)	-3.523	S6	1.220 (0.316)	-3.861
M2	-10.729 (2.376)	-3.714	S7	2.487 (0.297)	-3.261
M3	-5.322 (1.494)	-4.539	S8	4.644 (0.416)	-4.662
M4	-0.855 (0.927)	-5.407	S9	2.790 (0.439)	-3.102
M5	1.522 (0.789)	-6.151	S10	-0.760 (0.210)	-2.318
M6	3.911 (0.796)	-5.828	B1	-5.708 (1.074)	-3.154
M7	0.683 (0.983)	-5.425	B2	-0.501 (0.509)	-4.127
M8	2.219 (1.493)	-5.073	B3	-0.322 (0.563)	-3.701
M9	1.577 (2.173)	-4.700	B4	-1.772 (0.608)	-4.305
M10	10.524 (2.795)	-4.578	B5	-1.242 (0.776)	-4.240
S1	5.056 (0.891)	-2.682	B6	3.716 (0.635)	-5.267
S2	0.841 (0.609)	-3.961	B7	14.160 (0.591)	-3.682
S3	-0.888 (0.472)	-4.193	B8	14.385 (1.407)	-3.605
S4	1.706 (0.358)	-4.008	B9	15.641 (1.600)	-3.342
S5	2.730 (0.429)	-4.358	B10	15.842 (2.871)	-3.173
Mkt	0.799 (0.133)	-3.488			

Table 3 presents estimates of stochastic cointegration for 31 portfolios relative to aggregate consumption. In the column labeled "Cointegration," the cointegration measure, ϕ_i, is retrieved by performing the following regression:

$$d_{i,t} = \mu_i + \delta_i \cdot (t) + \phi_i c_t + \sum_{k=1}^{K} (\alpha_{-k} \Delta c_{t-k} + \alpha_k \Delta c_{t+k}) + \epsilon_{i,t}$$

where $d_{i,t}$ denotes the cash flow for portfolio i at time t, and c_t denotes aggregate per capita consumption of nondurables and services at time t. The column labeled "ADF" presents Dickey-Fuller statistics for the test of the null hypothesis that the cointegration residual contains a unit root. Data are converted to real using the CPI. The data are sampled at the monthly frequency and cover the period 7/1966-12/1999, for 402 observations. Robust standard errors are reported in parenthesis.

Table 4: **Monthly Cross-Sectional Regressions**

Panel A: Unconditional Models

Model	λ_0	λ_c	λ_g	λ_{vw}	λ_y	λ_{SMB}	λ_{HML}	$\bar{R}^2$
Leverage	0.623	0.028						0.475
	(0.036)	(0.005)						
Leverage	0.685	0.022						0.701
(Growth)	(0.254)	(0.007)						
CCAPM	0.946		-0.124					0.037
	(0.328)		(0.182)					
CAPM	1.382			-0.674				0.045
	(1.223)			(1.514)				
LCAPM	1.378			-0.680	-0.206			0.021
	(0.746)			(0.843)	(0.588)			
3-Factor	3.034			-2.295		0.025	-0.054	0.173
	(0.958)			(0.993)		(0.231)	(0.257)	

se=

Panel B: Conditional Models

Model	λ_0	λ_g	λ_{vw}	$\lambda_{g \cdot k}$	$\lambda_{k \cdot vw}$	$\lambda_{k \cdot y}$	$\bar{R}^2$	
Cond. CCAPM	1.117	-0.0286			-0.004			0.143
	(0.620)	(0.292)			(0.006)			
Cond. CAPM	1.552		-0.842			-0.038		0.106
	(0.694)		(0.791)			(0.076)		
Cond. LCAPM	1.714		-0.949	-0.176		-0.049	-0.008	0.196
	(0.775)		(0.885)	(0.735)		(0.053)	(0.007)	

Table 4 presents results for cross-sectional regressions, utilizing a set of 31 portfolios (10 size, 10 momentum, 10 book-to-market, and the value-weighted index). The results are obtained from a regression of average returns on risk measures,

$$\bar{r}_i = \lambda_0 + \lambda' \beta_i + \epsilon_i$$

where λ denotes a vector of risk premia. Parameters and robust standard errors are estimated in a single step via GMM. The factors utilized in the analysis are: 1) The log level of per capita consumption of nondurables and services, c, 2) Log rate of change in per capita consumption, g, 3) The value-weighted CRSP index return, vw, 4) The log rate of change in labor income, y, 5) The excess return on a portfolio of low market capitalization stocks over high market capitalization stocks, SMB, 6) The excess return on a portfolio of high book-to-market ratio stocks over a portfolio of low book-to-market ratio stocks, HML, and 7)-9) Cross-products of the conditioning variable, k, the consumption-wealth ratio with the growth in consumption, the value-weighted index return, and the growth in labor income. $\bar{R}^2$ represents the regression R^2 adjusted for degrees of freedom. The data cover the period 7/1966-12/1999, or 402 months, and are converted to real using the CPI.

Table 5: **Annual Cross-Sectional Regressions**

Panel A: Unconditional Models

Model	λ_0	λ_c	λ_g	λ_{vw}	λ_y	λ_{SMB}	λ_{HML}	$\bar{R}^2$
Leverage	8.206	0.275						0.661
	(0.349)	(0.036)						
CCAPM	13.065		1.111					0.179
	(3.777)		(0.668)					
CAPM	6.116			2.968				-0.023
	(6.957)			(7.992)				
LCAPM	14.875			-4.976	1.998			0.390
	(7.101)			(8.181)	(0.583)			
3-Factor	17.443			-8.214		1.446	-2.752	-0.043
	(5.963)			(6.529)		(2.749)	(3.007)	

Panel B: Conditional Models

Model	λ_0	λ_g	λ_{vw}	λ_y	$\lambda_{g\cdot k}$	$\lambda_{k\cdot vw}$	$\lambda_{k\cdot y}$	$\bar{R}^2$
Cond. CCAPM	13.672	0.939			-0.013			0.160
	(3.479)	(0.569)			(0.013)			
Cond. CAPM	8.551		0.342			0.187		0.009
	(6.648)		(7.679)			(0.081)		
Cond. LCAPM	11.282		-0.810	1.668		0.105	-0.205	0.363
	(5.709)		(6.608)	(0.473)		(0.077)	(0.013)	

Table 5 presents results for cross-sectional regressions, utilizing a set of 31 portfolios (10 size, 10 momentum, 10 book-to-market, and the value-weighted index). The results are obtained from a regression of average returns on risk measures,

$$\bar{r}_i = \lambda_0 + \lambda' \beta_i + \epsilon_i$$

where λ denotes a vector of risk premia. Parameters and robust standard errors are estimated in a single step via GMM. The factors utilized in the analysis are: 1) The log level of per capita consumption of nondurables and services, c, 2) Log rate of change in per capita consumption, g, 3) The value-weighted CRSP index return, vw, 4) The log rate of change in labor income, y, 5) The excess return on a portfolio of low market capitalization stocks over high market capitalization stocks, SMB, 6) The excess return on a portfolio of high book-to-market ratio stocks over a portfolio of low book-to-market ratio stocks, HML, and 7)-9) Cross-products of the conditioning variable, k, the consumption-wealth ratio with the growth in consumption, the value-weighted index return, and the growth in labor income. $\bar{R}^2$ represents the regression R^2 adjusted for degrees of freedom. The data cover the period 1967-1999, or 33 years and are converted to real using the CPI.

Table 6: Relative Merits of Consumption Leverage and Factor Models

Model	λ_0	λ_c	λ_g	λ_{vw}	λ_y	$\lambda_{g\cdot k}$	$\lambda_{k\cdot vw}$	$\lambda_{k\cdot y}$	λ_{SMB}	λ_{HML}	$\bar{R}^2$
FF	0.804	0.024		-3.206					-0.198	-0.221	0.819
	(0.299)	(0.006)		(1.551)					(0.785)	(1.077)	
Cond. CCAPM	0.726	0.023	0.054			-0.002					0.780
	(0.275)	(0.005)	(0.101)			(0.002)					
Cond. CAPM	0.828	0.023		-0.132			-0.014				0.775
	(0.451)	(0.005)		(0.516)			(0.011)				
Cond. LCAPM	0.704	0.024		-0.003	0.294		-0.015	0.000			0.776
	(0.483)	(0.005)		(0.533)	(0.188)		(0.011)	(0.002)			

Table 6 presents results for cross-sectional regressions, utilizing a set of 31 portfolios (10 size, 10 momentum, 10 book-to-market, and the value-weighted index). We augment the consumption leverage model (using the growth rate based model) to include additional factors: 1) the FF factors, vw, SMB, and HML; 2) the conditional CCAPM, with both the log rate of change in per capita consumption, g, and its cross product with the conditioning variable, k, the consumption-wealth ratio; 3) the conditional CAPM, with the vw market factor and its cross product with k; and 4) the conditional LCAPM, with the vw market factor, the log rate of change in labor income, y, and their cross products with k. All data are converted to real using the CPI.

Table 7: **Long Sample: 1926-1999**

Panel A: Summary Statistics

Portfolio	Mean Return	ϕ_i	Portfolio	Mean Return	ϕ_i
M1	0.0065	-12.070	S1	0.1433	12.613
M2	0.0526	-11.440	S2	0.1283	8.373
M3	0.0493	-5.354	S3	0.1157	4.184
M4	0.0710	-1.685	S4	0.1219	4.063
M5	0.0835	0.961	S5	0.1108	3.694
M6	0.0945	2.861	S6	0.1147	3.763
M7	0.1158	2.869	S7	0.1021	2.852
M8	0.1322	1.785	S8	0.0974	2.693
M9	0.1603	1.057	S9	0.0982	2.435
M10	0.1433	3.306	S10	0.0856	1.697
Market	0.0952	1.855			

Panel B: Unconditional Models

Model	λ_0	λ_c	λ_g	λ_{vw}	λ_{SMB}	λ_{HML}	$\bar{R}^2$
Leverage	7.195	0.534					0.689
	(0.466)	(0.081)					
CCAPM	7.305		2.959				0.166
	(4.333)		(1.257)				
CAPM	2.632			6.392			0.059
	(3.835)			(4.766)			
Three-Factor	19.720			-12.954	6.295	-10.325	0.120
	(4.918)			(5.560)	(2.057)		

Table 7 presents summary statistics and cross-sectional regression results for a sample of 21 portfolios over the period 1926 through 1999. The portfolios analyzed are ten portfolios sorted on the basis of past return (M1-M10), ten portfolios sorted on the basis of market capitalization (S1-S10), and the value-weighted CRSP index. Summary statistics for these data are presented in Panel A. Regression results for the specification

$$\bar{r}_i = \lambda_0 + \lambda' \beta_i + \epsilon_i,$$

where λ denotes a vector of risk premia, are presented in Panel B. The factors utilized in the analysis are: 1) The log level of per capita consumption of nondurables and services, c, 2) Log rate of change in per capita consumption, g, 3) The value-weighted CRSP index return, vw, 4) The excess return on a portfolio of low market capitalization stocks over high market capitalization stocks, SMB, and 5) The excess return on a portfolio of high book-to-market ratio stocks over a portfolio of low book-to-market ratio stocks, HML. $\bar{R}^2$ represents the regression R^2 adjusted for degrees of freedom. The data cover the period 1926-1999, or 75 years and are converted to real using the CPI.

Figure 1: **Dividend Series**

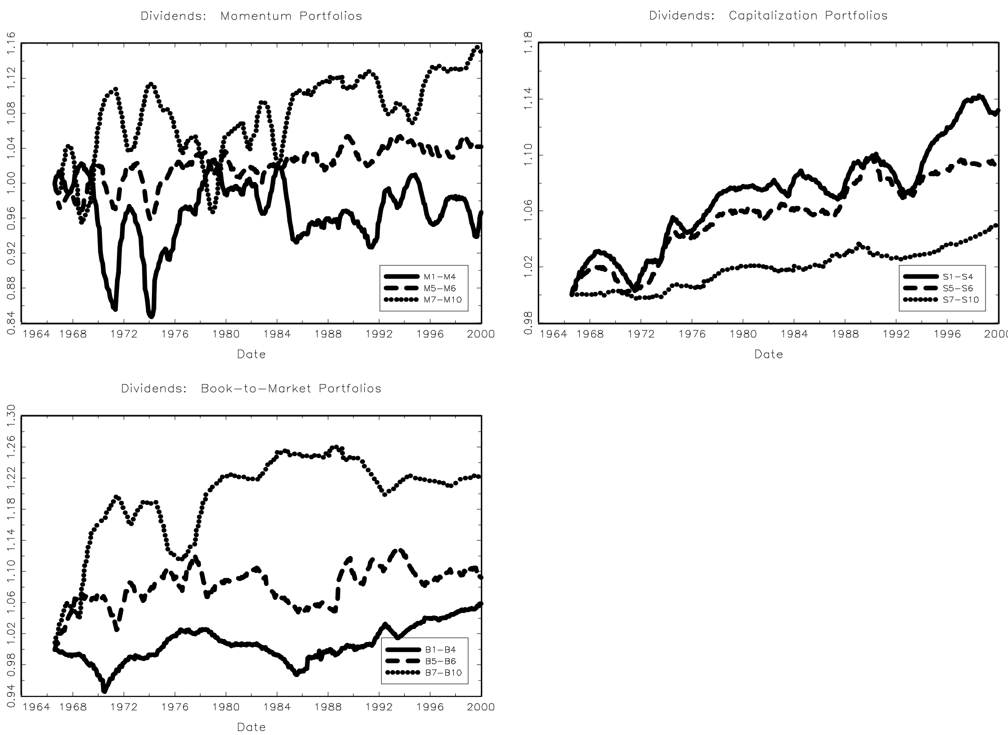

Figure 1 presents log dividend levels for the characteristic sorts over coarser portfolio partitions. M1-M4 represents the log dividend payment associated with the first through fourth momentum decile, M5-M6 represents the fifth through sixth decile, and M7-M10 represents the seventh through tenth decile. Labels for the size and book-to-market sorted portfolios are interpreted similarly. Data are converted to real using the CPI.

Figure 2: **Cash Flow Growth Trends**

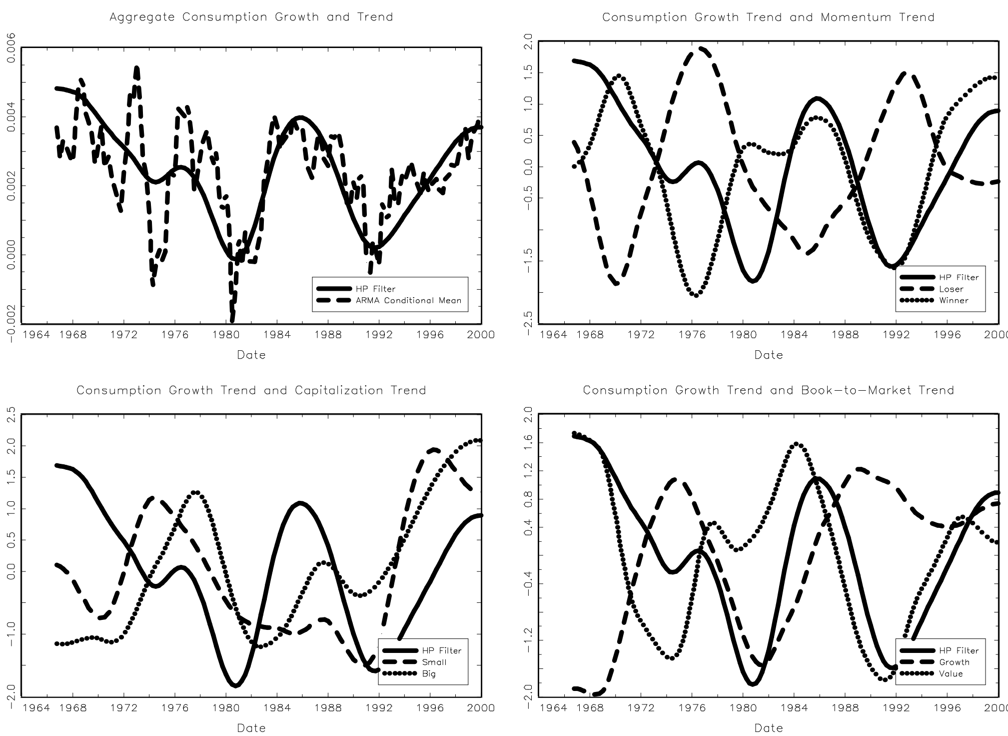

Figure 2 presents cash flow growth rates and trends for various series. The upper left panel presents Hodrick-Prescott filtered growth rates and the conditional mean of consumption growth, x_t, from estimation of the ARIMA (1,0,1) process for consumption growth:

$$g_{t+1} = \mu_c(1-\rho) + \rho g_t + \eta_{t+1} - \omega\eta_t$$

where g_t denotes log real consumption growth at time t. The upper right panel presents the HP-filtered consumption growth rate series and HP-filtered 1st and 10th momentum decile cash flow growth. The lower right panel presents HP-filtered consumption growth and HP-filtered 1st and 10th size decile cash flow growth. The lower left panel presents HP-filtered consumption growth and HP-filtered 1st and 10th book-to-market decile cash flow growth.

Figure 3: **Consumption Leverage Model**

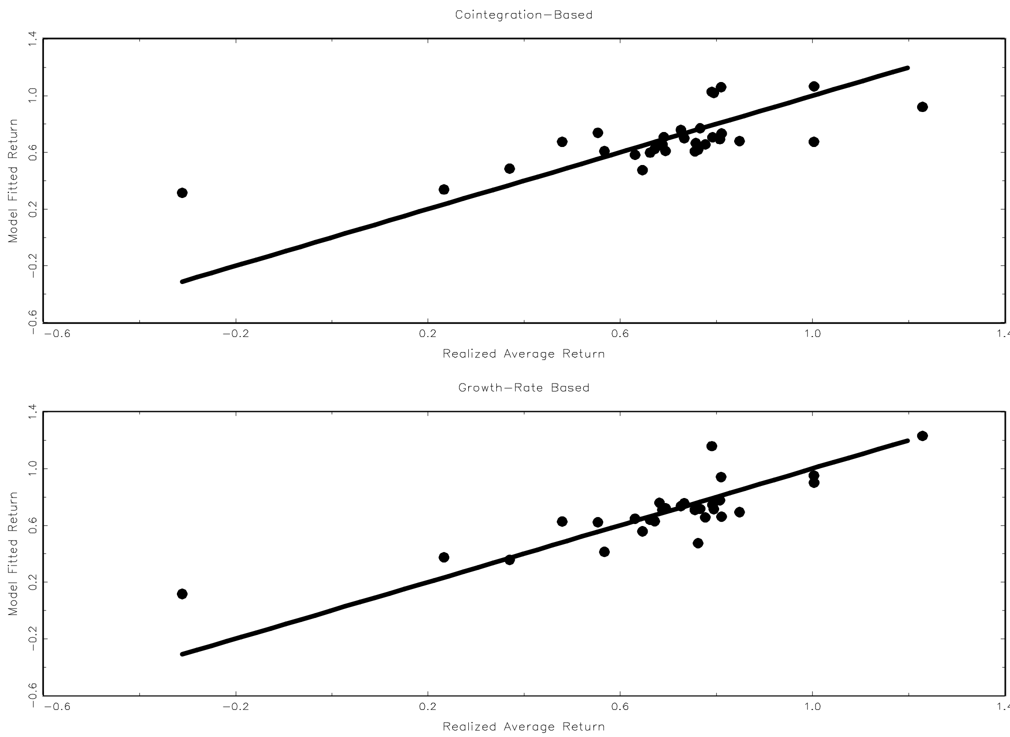

Figure 3 presents a scatterplot for the consumption leverage model estimated in the paper, where each point on the graph represents a portfolio with the realized average return on the horizontal axis and the fitted expected return on the vertical axis. The realized average return for each portfolio i is the historical time-series average of the portfolio return, and the fitted expected return is the fitted value for the expected return using the following cross-sectional regression parameter estimates:

$$E[R_i] \quad = \quad \lambda_0 + \phi_i \lambda_c$$

Thue upper panel presents fitted expected returns when the consumption leverage is measured via cointegration, whereas the lower panel estimates consumption leverage based on the ARMA (1,1) consumption growth rate specification. The straight line is the 45° line from the origin. Fitted and realized average returns are expressed in real terms.

Figure 4: **Unconditional Factor Models**

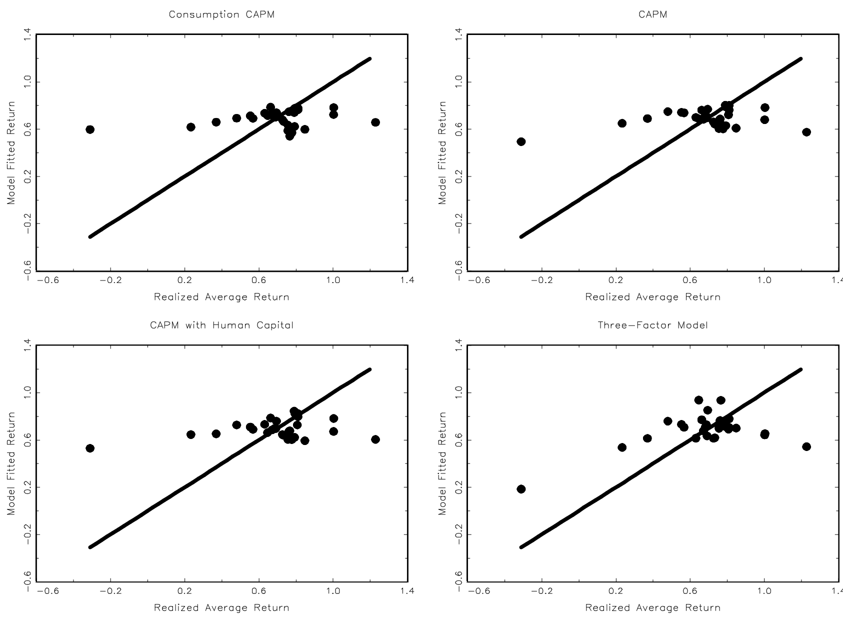

Figure 4 presents scatterplots for the unconditional models estimated in the paper, where each point on the graph represents a portfolio with the realized average return on the horizontal axis and the fitted expected return on the vertical axis. The realized average return for each portfolio i is the historical time-series average of the portfolio return, and the fitted expected return is the fitted value for the expected return using the following cross-sectional regression parameter estimates:

$$E[R_i] = \lambda_0 + \sum_{k=1}^{K} \beta_{i,k}\lambda_k$$

where $\beta_{i,k}$ represents the slope coefficient from a time series regression of the return on asset i on factor k. The factors k used in estimation of the risk measures, $\beta_{i,k}$ vary by plot. Clockwise from the upper left, the factors are: 1) The log rate of growth in per capita consumption, 2) The value-weighted market return ($R_{vw,t}$), 3) The value-weighted market return ($R_{vw,t}$) and the return on labor income ($R_{y,t}$), and 4) The market risk premium ($r_{vw,t}$), a size factor ($r_{SMB,t}$), and a value factor ($r_{HML,t}$). The straight line in each graph is the 45° line from the origin. Fitted and realized average returns are expressed in real terms.

Figure 5: **Conditional Factor Models**

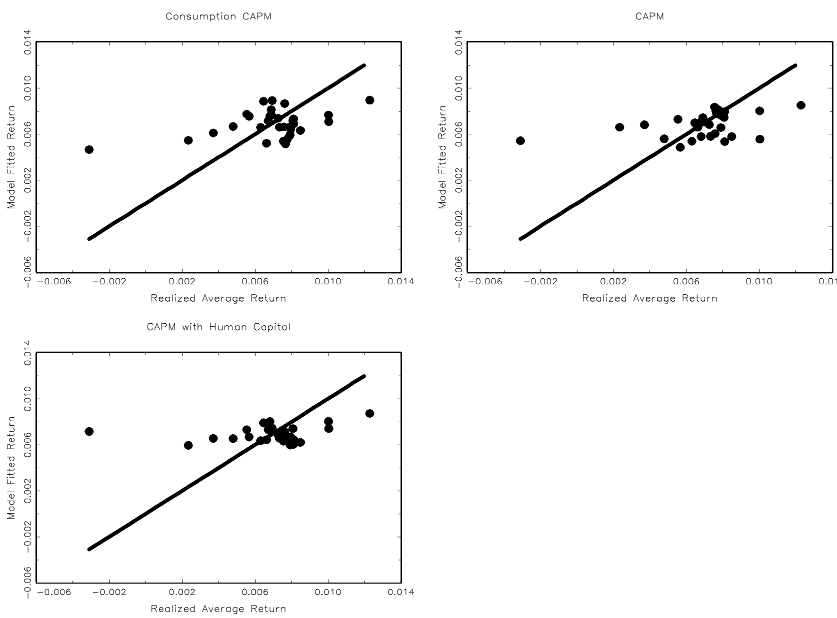

Figure 5 presents scatterplots for the conditional (scaled) models estimated in the paper, where each point on the graph represents a portfolio with the realized average return on the horizontal axis and the fitted expected return on the vertical axis. The realized average return for each portfolio i is the historical time-series average of the portfolio return, and the fitted expected return is the fitted value for the expected return using the following cross-sectional regression parameter estimates:

$$E[R_i] = \lambda_0 + \sum_{k=1}^{K} \beta_{i,k} \lambda_k$$

where $\beta_{i,k}$ represents the slope coefficient from a time series regression of the return on asset i on factor k. The factors k used in estimation of the risk measures, $\beta_{i,k}$ vary by plot. Clockwise from the upper left, the factors are: 1) The log rate of growth in per capita consumption and the product of consumption growth and the lagged consumption-wealth ratio, 2) The value-weighted market return ($R_{vw,t}$) and the product of the value-weighted market and the lagged consumption-wealth ratio, 3) The value-weighted market return, the return on labor income $R_{y,t}$, the product of the value-weighted market and the lagged consumption-wealth ratio, and the product of the return on labor income and the lagged consumption-wealth ratio. The straight line in each graph is the 45° line from the origin. Fitted and realized average returns are expressed in real terms.