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

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First Draft: July 2001
This Draft: October 2002

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Abstract

A common implication of general equilibrium models is that consumption betas determine the cross-section of risk premia. In addition, consumption beta's mirror differences in the exposure of the asset's dividends to aggregate consumption. These arguments suggest that differences in the exposure of dividends to consumption movements may contain information regarding the cross-sectional differences in risk premia. In this paper, we show that the long-run covariance between dividends and consumption account for a large proportion of the cross-sectional differences is risk premia on assets. We measure the long run covariance (i.e., cash flow beta) between consumption and dividends in two alternative ways. First, the regression coefficient from regressing dividend growth rates on a trailing moving average of consumption growth rates, and second, by the stochastic cointegration parameter between dividends and consumption. Cross-sectional differences in these measures of cash flow beta's account for more than 50% of the cross-sectional variation in risk premia across 30 portfolios—which include 10 momentum, 10 size, and 10 book-to-market sorted portfolios. Our empirical work shows that compensation for consumption risk is positive and highly significant. Our cash flow beta's, relative to benchmark models, are far more capable of justifying the differences in risk premia in the cross-section of assets. Monte Carlo evidence presented in the paper further corroborates our GMM based empirical evidence. In all, our work suggests the covariation of cash flows to low frequency movements in consumption contain important information regarding the risk premia on assets.

1 Introduction

The idea that differences in exposure to systematic risk should justify differences in risk premia across assets is central to asset pricing. The static CAPM (see Sharpe (1964), Lintner (1965)) implies that assets' exposures to aggregate wealth should determine cross-sectional differences in risk premia. The work of Lucas (1978) and Breeden (1979) argues that the risk premium on an asset is determined by its ability to insure against consumption fluctuations. Hence, the exposure of asset returns to movements in aggregate consumption (i.e., the consumption betas) should determine cross-sectional differences in risk premia. Evidence presented in Hansen and Singleton (1982, 1983) for the consumption based models, and in Fama and French (1992) for the CAPM, shows that these models have considerable difficulty in justifying the differences in rates of return across assets.[1] Consequently, identifying economic sources of risks that justify differences in the measured risk premia across assets continues to be an important economic issue.

An implication of general equilibrium models is that consumption betas are determined by preference parameters and the exposure of dividends to consumption. In particular, Abel (1999), Campbell (2000), and Bansal and Yaron (2000) present economic models where differences in consumption betas in the cross-section of assets mirrors differences in the exposure of the asset's dividends to consumption. Dividend flows which have larger consumption exposure (we label this the cash flow beta) have a larger consumption beta, and consequently also carry a higher risk premium. Using data on consumption and dividends, we directly measure the cash flow beta of 30 asset portfolios: 10 size, 10 book-to-market, and 10 momentum sorted portfolios. We show that the cross-sectional dispersion in the measured cash flow beta explains approximately 50% of the cross-sectional variation in observed risk premia. Further, the estimated market price of consumption risk is sizable, statistically significant, 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 Fama and French (1993) three factor model explains about 25% of the cross-sectional differences in the risk premia.[2]

[1] A voluminous literature over the past 20 years documents the difficulties of asset pricing models in explaining cross-sectional differences in measured risk premia. For an extensive recent survey see Campbell (2000)

[2] This is not surprising; Fama and French (1993) document that the dispersion in mean returns of mo-

We measure the exposure of a portfolio's dividend stream to consumption (the cash flow beta) in the time-series in two different ways. First, we measure the cash flow beta by the regression coefficient (OLS slope coefficient) of the future ex-post dividend growth rate on a moving average of past consumption growth rates. In the second approach, we measure the cash flow beta by the stochastic cointegration (see Campbell and Perron (1991) and Ogaki and Park (1998)) parameter between dividends and consumption. While our primary focus will be on the growth rate based regressions, our cointegration based approach produces similar empirical results.

We focus on size, book-market, and momentum sorted portfolios as the test assets. These assets form the basis of common risk factors used to explain differences in risk premia of other assets (see Fama and French (1993) and Carhart (1997)). Further, the dispersion in cross-sectional mean returns of these 30 assets is particularly challenging for many benchmark asset pricing models. In our empirical work, we also compare our model to alternative models proposed in the literature. In particular, we report results for the three factor Fama-French model, the static CAPM and the C-CAPM. Our empirical work estimates the time-series cash flow beta's and the cross-sectional price of consumption risk parameter jointly (using GMM), and hence our standard errors take account of the estimation error in all parameters.

As stated above, our single factor cash flow beta's developed in the paper can capture approximately 50% of the cross-sectional variation in risk premia. The price of consumption risk, the slope coefficient on the cash flow beta's in the cross-section of assets, is highly statistically significant. The point estimate is about 0.16 % (S.E.=0.053). The magnitudes of the cross-sectional R^2's and the measured price of consumption risk are very similar across the growth rate and cointegration based measures of cash flow beta's. Further, betas associated with benchmark factor models cannot explain the cross-sectional variation in risk premia. For example, the static CAPM and the C-CAPM can capture no more than 5% of the cross-sectional dispersion. In many cases, the premium associated with the risk factor is negative. In contrast to the single and multifactor models, our cash flow beta model *a priori* restricts the price of risk to be positive. In addition, our general equilibrium model provides an explicit mapping between the cash flow dynamics, the risk sources, and the betas, thus helping to interpret the empirical evidence.

To evaluate the our empirical evidence, we also conduct two Monte Carlo experiments:

mentum assets is particularly challenging for the their three factor specification.

one conducted under the null of the model and another under an alternative specification when all parameters of interest are zero. The finite sample distributions for the various parameters of interest, particularly the cross-sectional consumption price of risk parameter and adjusted R^2, further supports our GMM-based empirical evidence.

Our approach to measuring the cash flow beta is motivated by arguments presented in Hall (2001), Barsky and DeLong (1993), and Bansal and Lundblad (2002). These authors argue that small persistent predictable variation in aggregate economic growth rates is an important component in understanding asset price fluctuations. In all, our empirical evidence suggests that exposure to "low-frequency" components in consumption growth rates may indeed be an important source of systematic risk. Dividends of different assets have different exposures to this non-diversifiable source of risk; quantifiable differences in this exposure determine the cash flow beta and consequently the cross-section of risk premia. It is important to note (we provide this evidence) that measures of dividend-beta's based on regressing dividend growth rates on contemporaneous consumption growth rates capture little to none of the cross-sectional differences in risk premia. Hence, it seems that valuable information regarding mean rates of return on different assets is encoded in the exposure of dividends to low frequency movements in aggregate consumption.

Section 2 provides the solution for the cash flow beta model, as well as an analytical expression for the fundamental consumption beta (risk exposure). Section 3 provides data description and empirical evidence pertaining to the cash flow betas between. Section 4 details the ability of the dividend beta model to explain cross-sectional variation in risk premia and discusses our monte carlo evidence. Finally, Section 5 concludes.

2 Modeling Asset Returns

Our objective in this paper to show that the covariances between current dividend growth rates and long lags of consumption contain important information regarding the average returns on assets. The long run covariance can also be measured alternatively in levels via stochastic cointegration between dividends and consumption. In the following section, we present a general equilibrium model which motivates this empirical exercise. In particular, we show that an asset consumption beta is intimately related to the exposure of dividends to consumptions, and hence this exposure should contain information about the risk premia on assets. A related models is also considered in Campbell (2000), and Bansal and Yaron (2000). It is important to note that the broad economic implication that consumption betas are endogenous and mirror the differences in the consumption exposure of dividends is not unique to the model presented below; Abel (1999) presents a habit based model where the same holds true. Details of the model discussed below are in the appendix.

2.1 Asset Pricing Model

For the Epstein and Zin (1989) representative agent model the Intertemporal Marginal Rate of Substitution (IMRS) is,

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

G_{t+1} is the aggregate gross growth rate of consumption and $R_{c,t+1}$ is the total return on an asset that pays off aggregate consumption each period. Further, δ is a time preference parameter, ψ denotes the intertemporal elasticity of substitution, and $\theta \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$, where γ represents the coefficient of relative risk aversion.

The log of aggregate consumption c_t is assumed, as in Campbell (2000) and Bansal and Yaron (2000), to follow an ARIMA(1,1,1) process. The innovations in the univariate consumption process are η_t. Our consumption dynamics are designed to maintain a single factor of risk—the innovation in consumption growth.[3]

The log growth rate of consumption, $g_{t+1} = c_{t+1} - c_t$, is an ARMA(1,1),

$$g_{t+1} = \mu_c(1-\rho) + \rho g_t + \eta_{t+1} - \omega \eta_t \tag{2}$$

and 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:

$$x_t = (\rho - \omega) \sum_{j=0}^{\infty} \omega^j g_{t-j} \tag{3}$$

$$g_{t+1} = \mu_c + (x_t - \mu_x) + \eta_{t+1}, \tag{4}$$

[3]Multi-factor extensions are straightforward and are considered in Campbell (1996) and Bansal and Yaron (2000).

where μ_x is the unconditional mean of x_t. When ρ and ω are large (with $\rho > \omega$), then x_t is small in size and quite persistent. Barsky and DeLong (1993) and Hall (2001) argue that such small, persistent fluctuations in growth rates (the low frequency movements) are important for understanding asset price fluctuations. Note that when $\rho = \omega$ consumption growth is *i.i.d.*

2.2 Restrictions on the Risk Premia

The risk premium on any asset, where the return and the IMRS are log-normally distributed, is

$$E_t[R_{i,t+1} - R_{f,t}] = \beta_i[B_M \sigma_\eta^2] \tag{5}$$

where,

$$\beta_i = \frac{cov_t(r_{i,t+1}, \eta_{t+1})}{\sigma^2_{\eta_{t+1}}} \tag{6}$$

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 price of consumption risk. The magnitude of B_M is determined by the preference parameters and the dynamics of consumption (see appendix for details). The consumption beta of the asset determines the risk premium on the asset.

It is important to note that the beta of an asset is *not* an exogenous variable, rather it is determined in equilibrium by the exposure of the underlying dividends to aggregate consumption risk. To show this, we discuss alternative specifications that relate dividends to consumption.

2.3 Cash Flow Beta's: Growth Rates

In the context of a model of habits, Abel (1999) argues that the risk premium on different assets can be viewed as a result of differences in their dividend beta. He considers risk premia on assets where dividends (in logs) are expressed as $d_{i,t} = \varphi_i c_t$; φ_i is the cash flow beta of the asset. He shows that assets with larger φ also have larger risk premia.

To capture this intuition in growth rates, the relationship between dividends and consumption can be modeled using a growth projection:

$$d_{i,t+1} - d_{i,t} \equiv g_{i,t+1} = \delta_i + \varphi_i x_t + \eta_{i,t+1} \tag{7}$$

$$\varphi_i = \frac{cov(g_{i,t+1}, x_t)}{var(x_t)} \tag{8}$$

φ_i is a standard regression coefficient that measures the covariance between dividend growth and expected consumption growth. Note that $cov(g_{i,t+1}, x_t) = (\rho - \omega) \sum_{j=0}^{\infty} \omega^j cov(g_{i,t+1}, g_{t-j})$ –that is, φ_i reflects a measure of long run covariation between dividend growth and the history of consumption growth. We show below that an asset's beta depends on φ_i, its exposure to the predictable variation in the expected consumption growth rate x_t. It is worth noting that there is no significant change in the implications if one were to assume that consumption growth is $i.i.d$, but dividend growth depended on long lags of consumption growth.

Given the dynamics of the dividend growth, the arithmetic risk premium is determined by expression (5), where the consumption beta of the asset is

$$\beta_i = [\tau_i + \kappa_{i,1} A_{i,1}(\rho - \omega)] \tag{9}$$

and $A_{i,1} = \frac{\varphi_i - \frac{1}{\psi}}{1 - \kappa_{i,1}\rho}$ and τ_i is the regression coefficient of the residual in dividend growth rate projection (equation 8) on the consumption innovation. As can be seen, the beta of an asset is *not* exogenous. Rather, it is determined by the preference parameters and by the exposure of its dividend growth to consumption. An increase in the cash flow beta, φ_i, raises the risk premium on an asset. For simplification, we further assume that $\tau_i = \tau$. The dividend yield of a given asset in this model is not constant, and reacts to changing expected consumption growth rates.

2.4 Cash Flow Beta: Cointegration

In this section, we model consumption and dividends as stochastically cointegrated processes. Log dividends, $d_{i,t}$, and log consumption, c_t are related in the following manner:

$$d_{i,t} = \mu_i + \delta_i \cdot t + \phi_i c_t + \epsilon_{i,t} \tag{10}$$

In equation (10), ϕ_i describes the long-run stochastic relationship between consumption and dividends and is our alternative measure of cash flow beta. It is assumed that $d_{i,t}$ and c_t are I(1), but the departures from the relationship $\epsilon_{i,t}$, are I(0). This specification, as in discussed in Campbell and Perron (1991) Perron and Campbell (1993) and Ogaki and Park (1998), implies that asset-specific dividends and aggregate consumption are *stochastically cointegrated*. That is, ϕ_i measures the exposure of the stochastic trend in dividends to the stochastic trend in consumption. Note that with this notion of cointegration $d_{i,t} - \phi_i c_t$ may only contain a deterministic trend (i.e., no stochastic trend) if δ_i is different from zero.

The stochastic cointegration parameter ϕ_i can also be measured by first removing a deterministic time trend from the level of both c_t and $d_{i,t}$ and then utilizing the resulting detrended series to estimate ϕ_i. In practice we measure the ϕ_i's by deterministically detrending all the dividend and consumption series, and regressing the detrended dividends on a constant and the detrended consumption. Stochastic cointegration ensures that our estimated measure of cash flow beta ϕ_i, is not driven by deterministic trends in consumption and dividends, and does not simply reflect differences in mean dividend growth rates.[4] An additional motivation for detrending the data is that deterministic trends do not affect the risk premium as they are valued risk-neutrally. In economic terms what does ϕ_i measure? As shown in Phillips and Ouliaris (1990), ϕ_i provides a measure of the long run covariance between consumption and dividends.

Using stochastic cointegration to measure the cash flow beta is particularly valuable when one considers the possibility that both consumption and dividends are measured with error. Asymptotically, the presence of such measurement errors will not affect the estimates of the stochastic cointegration parameter, ϕ_i. Taking the first difference of equation (10), and substituting the assumed consumption growth rate process (4), it follows that

$$g_{i,t+1} = \delta_i + \phi_i x_t + \phi_i \eta_{t+1} + \epsilon_{i,t+1} - \epsilon_{i,t} \tag{11}$$

[4]Note that in equation (10), if δ_i is set to zero, then it follows that $d_{i,t}$ and c_t are fully cointegrated. In this case the estimated ϕ_i (with δ_i set equal to 0) would equal the ratio of the mean dividend growth rate relative to mean consumption growth rate (see discussion in Hamilton (1994)). By deterministically detrending d_t and c_t and then using the resulting detrended series to run a cointegration regression to estimate ϕ_i, we ensure that this parameter is estimated by the exposure of the stochastic trend in dividends to the stochastic trend in consumption. In other words, deterministic trends do not play a role in the estimation of ϕ_i.

Using equation (11), it is shown in the appendix that the consumption beta of the asset is

$$\beta_i = [\phi_i + \kappa_{i,1} A_{i,1}(\rho - \omega)] \quad (12)$$

Hence, as in the growth rate specification, the asset's beta reflects its cash flow exposure to consumption.

2.4.1 Cross-Sectional Restrictions

The asset's consumption beta, in conjunction with the restriction on the asset risk premium (see equation (5)), leads to cross-sectional implications for risk premia. Typically, these cross-sectional restrictions are tested by regressing the average return on a constant and the beta on the asset. Given the link between the cash flow exposure to consumption and the beta of the asset, the same theoretical restrictions can be tested by a cross-sectional regression on the cash flow beta directly. 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.

The perfect correlation between φ_i and β_i implies that the cross-sectional regression of the average return on a constant and φ_i, provides the same predicted (i.e, theoretical) mean return as a cross-sectional regression of the average return on β_i. Further, the R^2 in the cross-sectional regression based on φ_i is equal to that from using β_i directly. Consequently, substituting the consumption beta, equation (9), into the expression for the risk premium, equation (5), leads to the following cross-sectional regression,

$$E[R_{i,t}] = \lambda_0 + \varphi_i \lambda_c. \quad (13)$$

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 dividend beta directly obviates the need to estimate additional preference and consumption growth rate parameters that go into the construction of β_i; these parameters, as stated above, do not alter the predicted (theoretical) mean return for various assets. Equation (13) will be used extensively to evaluate the empirical plausibility of the cash flow beta model. The above logic directly applies to the cointegration based measures of cash flow beta as well, the only difference being that we replace φ_i in equation (13) with ϕ_i.

3 Cash Flow Dynamics

3.1 Data

3.1.1 Aggregate Cash Flows and Factors

In our empirical tests, we consider the ability of the cash flow beta model stated in equation (13), as well as alternative pricing models, to capture cross-sectional variation in average returns. Our empirical exercise is conducted on data sampled on a quarterly frequency. Following many past studies [e.g. Hansen and Singleton (1983)], we define aggregate consumption as seasonally adjusted real per capita consumption of nondurables plus services. The quarterly real per capita consumption data are taken from the NIPA tables available from the Bureau of Economic Analysis. To convert returns and other nominal quantities, we also take the associated personal consumption expenditures (PCE) deflator from the NIPA tables. The mean of the inflation series is 0.0113 per quarter with a standard deviation of 0.0065. The mean of the quarterly real consumption growth rate series over the period spanning the 3rd quarter of 1967 through the 4th quarter of 1999 is 0.0052 with standard deviation of 0.0045.

The alternative 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), 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 per capita consumption. The priced source of risk in the CAPM is the return on a value-weighted index of stocks, obtained from CRSP. 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.[5] Market capitalization and return data are taken from CRSP, and book values are formed from Compustat data.

Throughout the paper, all of the coefficients and standard errors of both the time series and cross-sectional parameters are calculated via GMM; all of the risk exposures (φ_i or β_i) and cross-sectional risk prices are jointly estimated in one step (see Appendix for details). The GMM procedure that we follow is similar to that proposed in Cochrane (2001).

3.1.2 Benchmark Portfolios

The portfolios employed in our empirical tests sort firms on dimensions that lead to cross-sectional dispersion in measured risk premia. The particular characteristics that we consider are firms' market value, book-to-market ratio, and past returns (momentum). Our rationale for examining portfolios sorted on these characteristics is that size, book-to-market, and momentum based sorts are the basis for factor models examined in Fama and French (1993) and Carhart (1997) to explain the risk premia on other assets. Consequently, understanding the risk premia on these assets is an economically important step towards understanding the risk compensation of a wider array of assets. We focus on one-dimensional sorts on these characteristics as this procedure typically results in over 150 firms in each decile portfolio and over 300 firms in each quintile portfolio. To better measure the consumption exposure of dividends, it is important to limit the portfolio specific variation in dividend growth rates, and a larger number of firms in a given portfolio helps to achieve this.

Market Capitalization Portfolios

We form a set of portfolios on the basis of market capitalization. The set of all firms covered by CRSP are ranked on the basis of their market capitalization at the end of June of each year using NYSE capitalization breakpoints. In Table 1, we present means and standard deviations of market value-weighted returns for size quintile portfolios. The data evidences a small size premium over the sample period; the mean real return on the lowest quintile firms is 247 basis points per quarter, contrasted with a return of 221 basis points per quarter for the highest quintile. The means and standard deviations of these portfolios are similar to those reported in previous work.

[5] For more detail on the formation of these factors see Fama and French (1993).

Book-to-Market Portfolios

Book values are constructed from Compustat data. 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 $t-1$.[6] All firms with Compustat book values covered in CRSP are ranked on the basis of their book-to-market ratios at the end of June of each year using NYSE book-to-market breakpoints. Sample statistics for these data are also presented in Table 1. The data evidence a higher book-to-market than size spread; the highest book-to-market firms earn average real quarterly returns of 306 basis points, whereas the lowest book-to-market firms average 215 basis points per quarter.

Momentum Portfolios

The third set of portfolios investigated are portfolios sorted on the basis of past returns. Jegadeesh and Titman (1993) use NYSE and AMEX listed firms to document that a "momentum" strategy that purchases the best-performing firms and shorts the worst over a past horizon earns a substantial profit. To construct our momentum-based portfolio returns, we follow a procedure analogous to Fama and French (1996) and sort CRSP-covered NYSE and AMEX firms on the basis of their cumulative return over months $t-12$ through $t-1$. Summary statistics for value-weighted portfolios formed at time t on the basis of these past returns are presented in Table 1. As shown, this sort provides the highest dispersion in mean returns among the firm characteristics. The highest quintile firms earn an average real return of 342 basis points per quarter, whereas the lowest quintile firms earn an average real return of 48 basis points per quarter. The spread of 294 basis points and the reported volatility of returns is comparable to the data in Fama and French (1996).

3.2 Portfolio Dividends

To explore the long-run relationship between portfolio cash flows and consumption, we also need to extract dividend payments associated with these value-weighted portfolios. Our construction of the dividend series is the same as that in Campbell (2000). Let the total return per dollar invested be

$$R_{t+1} = h_{t+1} + y_{t+1}$$

[6] We thank Ken French for providing us the book to market-sorted portfolio data. For a detailed discussion of the formation of the book to market variable, refer to Fama and French (1992).

where h_{t+1} is the price appreciation and y_{t+1} the dividend yield (i.e., dividends at date $t+1$ per dollar invested at date t).[7] We observe R_{t+1} and the price gain series h_{t+1} for each portfolio; hence, $y_{t+1} = R_{t+1} - h_{t+1}$. The level of the dividends we use in the paper is computed as

$$D_{t+1} = y_{t+1} V_t$$

where

$$V_{t+1} = h_{t+1} V_t$$

with $V_0 = 100$. Hence, the dividend series that we use, D_t, corresponds to the total dividends given out by a mutual fund at t that extracts the dividends and reinvests the capital gains. The ex-dividend value of the mutual fund is V_t and the per dollar return for the investors in the mutual fund is

$$R_{t+1} = \frac{V_{t+1} + D_{t+1}}{V_t} = h_{t+1} + y_{t+1}$$

From this equation, it is evident that V_t is the discounted value of the dividends that we use.

We construct the level of the dividends D_t for all the portfolios on a monthly basis. From this we construct quarterly levels of dividends by summing the level of dividends within a quarter. As the dividend yields have strong seasonalities, we employ a trailing four quarter average of the quarterly dividends to construct the deseasonalized quarterly dividend series. This procedure is consistent with the approach in Hodrick (1992), Heaton (1993), and Bollerslev and Hodrick (1995). These series are converted to real by the personal consumption deflator. Log growth rates are constructed by taking the log first difference of the quarterly deseasonalized series. Summary statistics for the dividend growth rates of the portfolios under consideration are presented in Table 1. An analogous construction is applied for decile portfolios; summary statistics for these portfolios are presented in Table 2.

[7] To be precise, h_{t+1} represents the ratio of the value at time $t+1$ to time t, $\frac{V_{t+1}}{V_t}$, and y_{t+1} represents the total dividends paid by the firm at time $t+1$ divided by firm value at time t, $\frac{D_{t+1}}{V_t}$.

4 Empirical Evidence

4.1 Measuring the Consumption Exposure of Dividends

To measure the time-series relationship between dividends and consumption, we consider the following regression:

$$g_{i,t+1} = \delta_i + \varphi_i x_t + \eta_{i,t+1} \tag{14}$$

where $g_{i,t+1} = d_{i,t+1} - d_{i,t}$ and φ_i measures the covariance between portfolio dividend growth and x_t. Given x_t, φ_i is estimated by exploiting standard GMM orthogonality conditions of the error term with x, the details of which are provided in the appendix. We construct x_t as a simple trailing eight-quarter moving average of past real consumption growth. We also document evidence at different lengths of smoothing.[8] Hence, the consumption exposure of dividends is measured as

$$\varphi_i = \frac{K \sum_{j=1}^{K} cov(g_{i,t+1}, g_{t+1-j})}{Var(\sum_{j=1}^{K} g_{t+1-j})}$$

with K being the length over which consumption growth is smoothed.

To measure the cash flow beta, ϕ_i, via stochastic cointegration, we first detrend the log consumption and dividend series by separately regressing the log level of consumption and the log level of dividends on a constant and a time trend. The resulting de-trended time series, c_t^* and d_t^*, are then used to measure ϕ_i. More specifically, we follow Stock and Watson (1993), and use dynamic least squares (DOLS) to estimate ϕ_i, that is we estimate ϕ_i via

$$d_{i,t}^* = \mu_i + \phi_i c_t^* + \sum_{k=1}^{K} \left(\alpha_{-k}\Delta c_{t-k}^* + \alpha_k \Delta c_{t+k}^*\right) + \epsilon_{i,t} \tag{15}$$

with $K = 4$. By first deterministically detrending consumption and dividends, and then using the de-trended series to measure ϕ_i, we ensure that deterministic trends in dividends and consumption do not drive our measures of ϕ_i.

Estimates of φ_i for the characteristic-sorted quintile portfolios are presented in Table 1. As shown in the table, a clear pattern emerges in the covariance of portfolio dividend

[8] We also estimate an ARMA (1,1) for the consumption growth series from 1967.3 to 1999.4. The AR(1) parameter estimate of this process is 0.730 (S.E.=0.116) and the MA(1) estimate is 0.404 (S.E.=0.178). The 8 quarter smoothed consumption growth series and the conditional mean time-series implied by the estimated ARMA process for consumption growth have a correlation of about 90%.

growth rates with the smoothed consumption growth rate. Sorting on past returns produces extremely large dispersion in φ; the sensitivity of winner portfolio dividend growth to consumption growth is 9.33 (S.E. 5.71) compared to -2.65 (S.E. 5.50) for the loser portfolio. Book-to-market sorts also produce a large spread; the high book-to-market firms' sensitivity to consumption growth is 5.58 (S.E. 2.88) compared to -0.83 (S.E. 1.82) for the low book-to-market firms.

The evidence based on cointegration exactly mirrors this pattern. In particular, the loser portfolio and the low book-to-market portfolios have small ϕ's and low mean returns, while the opposite is true for the high mean return portfolios. As a measure of the empirical content of the economic argument, note that in Table 1 panel B we report results from regressing the mean returns on the cash flow beta measures. Throughout the paper, all risk prices are expressed in quarterly percentage terms. For the growth rate based dividend beta, the cross-sectional R^2 is 58%, and it is 68% for the cointegration based measure. The slope coefficients in both cases are positive and highly significant. The quarterly compensation for consumption risk is 0.17% (S.E. 0.05) for the growth rate case and 0.15% (S.E. 0.03) in case of cointegration. Hence the key parameter of interest, the price of risk, is very precisely estimated. For a benchmark comparison, the three factor FF model has a cross-sectional R^2 of 11% for these 15 assets.

The summary statistics illustrate an important point; portfolios with high (low) φ_i are portfolios with high (low) average returns. That is, portfolios with higher long run covariance with consumption have larger risk premia. To analyze this relationship further, we display the extreme portfolio dividend growth rates and the smoothed consumption growth rate in Figures 1-3. In accordance with the large estimated φ's, the winner and high book-to-market portfolio dividend growth rates demonstrate a close relationship to the smoothed consumption growth rate, generally falling during documented recessions and rising during consumption booms. However, the loser portfolio dividend growth rates demonstrates strong counter-cyclical movements. These plots suggest that the momentum and book-to-market portfolios are sorting along macroeconomic exposures across firms. Capitalization-sorted portfolios also demonstrate this pattern with respect to consumption, with the estimated cash flow beta coefficient on small firms exceeding the large firms, but the difference is less pronounced in accordance with the reduced size premium observed in more recent years.

The long run covariances between dividends and consumption, as measured by ϕ_i are estimated with considerable error. This is not surprising, and in the univariate context

Campbell and Mankiw (1987) highlight the great difficulties in precisely measuring the long run response. The long run response of dividends to a unit standard deviation shock in consumption is $\sigma_\eta \phi_i$. The proportion of the unconditional variance of dividend growth rates that can be accounted for by the variance of the long run response is $\frac{\sigma_\eta^2 \phi_i^2}{var(d_{i,t} - d_{i,t-1})}$. For the extreme looser portfolio (i.e, M1-2) that is about 3% and for the extreme winner portfolio (i.e., M9-10) it is 15%. These small magnitudes indicate that most of the variation in dividends is unrelated to consumption movements. The growth rate measures, φ, are also estimated with large standard errors. The associated low time-series R^2's suggest that a significant portion of variation in dividend growth rates is unrelated to low frequency movements in consumption growth. It is important to note that in both cases, the cross-sectional price of risk λ_c, is positive and estimated very precisely. Further, the cross-sectional R^2 is in excess of 50%. Despite the time-series imprecision, our cash flow beta's explain a large portion of the differences in the risk premia *across* assets.

In section 4.3, we report detailed Monte Carlo evidence which provides additional insight into our empirical evidence. In particular, we provide a finite sample empirical distribution for λ_c and the cross-sectional R^2, when we assume that there is no relationship between consumption, dividends, and expected returns. These distributions shows that our significant estimates of λ_c and high cross-sectional R^2 are very unlikely to be an outcome of such a model; in other words, our cross-sectional estimates are very significant. In a second Monte Carlo, we exploit our economic model directly, where dividends, consumption, and expected returns are connected through the cash flow beta. In this experiment, the standard errors on the cash flow beta's will be large, comparable to those observed in the data, in finite samples. However, the key parameters of interest, the cross-sectional R^2 and λ_c, will be very precisely estimated. Even in finite samples of 130 observations, there is little-to-no bias in the estimate of the cash flow beta, hence these beta's continue to provide very valuable information regarding differences in mean returns. In general, the economic value of the cash flow beta's should be determined by their ability to explain cross-sectional differences in measured risk premia. For comparison, market betas are estimated with precision in the time-series; however, these betas provide little economic information regarding dispersion in the mean returns across assets.

4.2 Equity Risk Premia in the Cross-Section

In this section, we examine the relative performance of our cash flow beta model and standard unconditional factor models, in explaining the cross-section of equity risk premia. To have a larger number of cross-sectional observations we consider a finer sort of the portfolios detailed above. We form 30 portfolios (10 size, 10 momentum, and 10 book-to-market); summary statistics for these portfolios are presented in Table 2. As exhibited in the table, this finer sort exhibits similar cross-sectional patterns in risk exposures and mean returns as the quintile sort analyzed above.

4.2.1 Performance of Cash Flow Beta Model

We begin our exploration by examining the ability of our cash flow beta model presented above to explain the cross-section of equity returns. The cross-sectional risk premia restriction is stated in equation (13), with λ_0 and λ_c as the cross-sectional parameters of interest.[9] Table 3 (Panel A) documents the cross-sectional performance of the cash flow model. The results show that the risk price is positive and significant— the estimated price of consumption risk λ_c is 0.167 (S.E. 0.053). Further, the adjusted R^2 is 51%, suggesting that the fundamental model can explain a considerable portion of the equity risk premia associated with this set of portfolios. The estimated risk measures, φ_i, are reported in Table 4. This evidence is depicted graphically in Figure 4, which plots the predicted expected returns against the realized mean returns. As before, all estimation is conducted using one step GMM, hence the uncertainty in estimating the cash flow bets's are reflected in the standard errors of the price of risk. Using cointegration to measure the cash flow betas produces results that are very similar to our growth rate based risk measures.

A particular success of the model is that it is capable of explaining much of the variation across momentum returns. This dimension is particularly challenging for the alternative models considered. However, the model's success is not limited to this dimension; the correlation between the risk measures (φ_i) and the average returns are 94% for momentum, 41% for size, and 71% for book-to-market. These results are particularly intriguing since the model's estimates of risk measures are based solely upon the relation between cash flows

[9]Note that in the case where the cash flow beta is estimated via the co-integration approach, based on Engle and Granger (1987), we ignore the estimation error in estimating the superconsistent cash flow beta, ϕ_i.

and consumption.

In Table 4, we also show that the contemporaneous covariance between dividend growth rats and consumption provides virtually no information regarding the cross-section of average returns. These consumption beta's, as documented in Table 4 (Panel B1), yield an insignificant and negative price or risk and a zero cross-sectional R^2. In contrast, dividend growth covariance with smoothed 4 and 8 quarter consumption growth helps to explain a considerable portion of the cross sectional difference in risk premia. The evidence in Table 4 shows that dividend growth rate covariances with moderate to long lags of consumption growth contain valuable information regarding the cross-section of risk premia. This evidence, along with the cointegration based estimates, indicates that dividend exposures to low frequency movements in consumption is economically important for understanding differences in risk premia across assets.[10]

4.2.2 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. Table 3 (Panel A) documents the results of cross-sectional regressions in the context of standard unconditional models: the C-CAPM, the CAPM, 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, $R_{SMB,t}$, 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 premium restriction is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{g,i}\lambda_g \tag{16}$$

[10] Daniel and Marshall (1997) argue that at longer horizons, a habits-based model can better justify the risk premium on the (value-weighted) market portfolio and the risk free rate. They argue that the measurement errors in consumption may be the reason for the poor performance of the model at shorter horizons.

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. The estimated price of consumption risk, λ_g, is positive and statistically significant, but the adjusted R^2 of 4.6% suggests that this model explains some, but not a substantial portion of the cross-sectional variation in average returns. The inability of the unconditional C-CAPM to explain the portfolio returns is depicted graphically in Figure 4.

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 premium restriction

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw} \tag{17}$$

where $\beta_{vw,i}$ describes an asset's exposure to market risk, and λ_{vw} describes the price of market risk. As in previous studies, the estimate of λ_{vw} is negative and not statistically significant. Further, the ability of the model to explain cross-sectional risk premia is limited, as demonstrated in the relatively low adjusted R^2 of 3.0%. Again, the difficulty of the static CAPM in explaining the cross-section of equity market returns is displayed graphically in Figure 4.

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

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw} + \beta_{SMB,i}\lambda_{SMB} + \beta_{HML,i}\lambda_{HML} \tag{18}$$

This model exhibits substantial improvement over the single-factor models in explaining cross-sectional variation in returns, as the adjusted R^2 rises to 24.3%. However, with the exception of the market risk premium, the model parameters are imprecisely estimated. A graphical depiction of the model fit is provided in Figure 4.

4.3 Monte Carlo Analysis

As noted earlier, the cash flow beta's are imprecisely measured in the time series even though the key cross-sectional parameter, λ_c, is estimated precisely, and cash flow beta's explain more that 50 % of the cross-sectional dispersion in expected returns. In this section, we discuss two Monte Carlo experiments that provide a finite sample empirical distribution for the various parameters of interest. These experiments show that our empirical results reflect economic content rather than some random chance.

We consider two Monte Carlo experiments. In the first experiment, we simulate 10,000 samples of 130 quarterly time series observations of aggregate consumption growth. This experiment is termed the "Alternative" as it simulates under the alternative hypothesis that our model is incorrect, assuming that the price of consumption risk and the cash flow beta's, φ_i, are zero. Consumption is modeled as an i.i.d. process $\hat{g}_{t+1} = \mu + \eta_{t+1}$ with $\mu = 0.0052$ and, on an annualized basis, $\sigma_\eta = 0.0090$.[11] As in the empirical analysis above, we smooth the resulting simulated consumption growth rates over eight quarters and project the *observed* dividend growth rates on the resulting smoothed consumption growth, $\hat{x}_t$:

$$d_{i,t+1} - d_{i,t} = \hat{\mu}_i + \hat{\varphi}_i x_t + \hat{\eta}_{i,t+1} \tag{19}$$

and regress *observed* average returns on the resulting risk measures, $\hat{\varphi}_i$:

$$\bar{R}_i = \hat{\lambda}_0 + \hat{\lambda}_c \hat{\varphi}_i + \hat{u}_i \tag{20}$$

As in the empirical analysis, risk measures and risk premia are estimated in a single step GMM procedure. Note that the population values of the φ_i's are zero, and the population value of λ_c is correspondingly also zero. Hence, this Monte Carlo experiment provides the finite sample empirical distribution for λ_c, the R^2 for the cross-sectional projection, and the φ_i's when the population values for all these quantities is zero.

The results of this experiment are presented in Table 5. The distribution of the estimates of φ_i and their accompanying R^2 are presented in Panel A. The φ_i's are estimated with considerable error, but the distributions are centered at the population values. The distribution for the price of risk parameter, λ_c, and the cross-sectional adjusted R^2 are presented in Panel B. This distribution for the risk price is essentially centered at zero (the population value), and suggests that our point estimates in the data of 0.167, as well as the cross sectional $\bar{R}^2$ of 51.0%, are in the right tail of the distribution. The empirical price of risk is above the 97.5% critical value, whereas the empirical $\bar{R}^2$ exceeds the 85% critical value. The experiment

[11] In untabulated results, we model consumption growth as an ARMA (1,1) process, $g_{t+1} = \mu + \rho x_t + (\rho - \omega)\eta_{t+1}$, with $\rho = 0.730$ and $\omega = 0.404$. The Monte Carlo results are materially unchanged under these assumptions.

suggests that the empirical results of the paper reflect economic content rather than random chance. In an economy in which asset returns and dividend growth are independent of consumption growth, the probability of observing the magnitudes of λ_c and the cross-sectional $\bar{R}^2$ that we find in the data are extremely low.

Our second Monte Carlo experiment assumes the null hypothesis that our model is correct. Again, we simulate 10,000 samples of 130 quarterly observations of a consumption growth process. We assume that consumption growth follows an ARMA (1,1) process, $g_{t+1} = \mu + \rho x_t + (\rho - \omega)\eta_{t+1}$, with $\mu = 0.0052$, and the annualized standard deviation of the innovation, $\sigma_\eta = 0.0082$. The ARMA parameters are chosen to match empirical values; $\rho = 0.730$ and $\omega = 0.404$. The empirically estimated φ_i (reported in table 4) are used to generate portfolio dividends:

$$\hat{d}_{i,t+1} - \hat{d}_{i,t} = \mu_i + \varphi_i \hat{x}_t + \eta_{i,t+1} \tag{21}$$

where $\hat{x}_t$ represents an eight quarter moving average of the simulated consumption growth. The vector of μ_i's and σ_{η_i}'s are chosen to match the empirically observed mean and covariance structure of dividends. The population R^2's for the time series regressions are reflective of the very low R^2's that we observe. We then generate portfolio returns using expressions (42) and (43) in the Appendix, with the preference parameters γ and ψ chosen to match $\lambda_c = 0.167$, as observed empirically. Resulting mean excess returns are regressed on the risk measures:

$$\hat{\bar{R}}_i = \hat{\lambda}_0 + \hat{\lambda}_c \varphi_i + \hat{u}_i \tag{22}$$

Risk measures and risk premia are estimated in a single step via GMM.

We present the distribution of risk measures, risk premia, and cross-sectional adjusted R^2 in Table 6. The distribution of the risk measures is presented in Panel A. The growth rate based cash flow beta's, φ_i, are measured without bias, matching their population values on average, but are highly dispersed. As in the previous Monte Carlo experiment, the bottom momentum decile portfolio displays a wide range of estimates of φ_i, ranging from a 10% critical value of -14.10 to a 90% critical value of 5.70. The large time series standard errors we observe empirically are to be expected—the population variance of the residual is very large (this mirrors what we document in Table 1) hence the time-series $\bar{R}^2$'s are very low. The distribution of the price of risk parameter, λ_c, predictably captures a downward bias, as in a finite sample the beta's are measured with sampling error. Hence, the mean value of λ_c is below its population value of 0.167. Note however, that the 95% range for λ_c in finite samples is quite precise. The 2.5% critical value is about 0.09 and the 97.5% critical value is 0.12. The typical hypothesis of interest that λ_c equals zero would be sharply rejected. Despite estimating the time-series dividend beta's with large standard errors, the cross-sectional dimension of the model will capture the truth—the price of risk parameter will be significantly different from zero, and the cross-sectional $\bar{R}^2$ will be far from zero. The downward bias in estimating λ_c suggests that relative to our point estimate of 0.167 in the data, the price of risk and the cross-sectional $\bar{R}^2$ are likely to be higher.

Under the null of the cash flow beta model, we also consider one additional experiment. Increasing the variance of the residual, $\eta_{i,t+1}$, in finite samples induces greater estimation error in the estimation of the cash flow betas. Hence, one can also ask at what magnitude for the residual variance will make it virtually impossible to learn about the $\varphi's$ is finite samples, so that λ_c is not significantly different from zero. Our evidence (not reported in tables) suggest that in samples of 130 time-series observations, this occurs when the variance of the dividend growth rates is approximately 4 times the observed quantities in the data. Stated differently, in our data, one can still reliably learn about the relation between expected returns and the cash flow beta's—as we do in the data.

4.4 Discussion and Additional Robustness Checks

It is worth noting that standard consumption based models 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 difficulty in explaining risk premia in the cross-section. Hence, in the presence of measurement error, there is every reason to believe that the standard return-based consumption betas will fail to capture the important exposures facilitated by our regression methodology. For example, we find that the correlation between the estimated consumption beta (using returns) and the growth rate based exposures (φ_i) is 0.21. Within the sorting dimensions, this correlation is 0.21 for momentum, 0.37 for size, and 0.64 for book-to-market. If there are considerable errors or other difficulties in measuring the appropriate level of consumption (as argued in Campbell (1993)), then indeed the usual consumption beta may be a poor estimate of the true consumption beta that is needed to explain risk premia. Our measures of cash flow beta are fairly robust to stationary measurement errors in consumption and dividends. As discussed earlier, stochastic cointegration relations are unaffected by stationary measurement error; further, even our growth rate projections employing a moving average of consumption growth rates mitigate the contaminating effects of mis-measuring consumption.

An additional possibility is that the one factor C-CAPM is simply misspecified. For expositional ease, we have reported the economic model where there is a single shock. However, consumption may be made of many independent latent components. With Epstien-Zin preferences, this would imply that return covariances with these individual components of consumption, and not aggregate consumption per se, will determine risk premia.

What are the effects, if any, of using alternative weights to compute the long run growth rate covariance and of using longer horizon covariances? At longer horizons, measurement of covariances in small samples can be biased (see Campbell and Mankiw (1987), amongst others). To explore this further, we have computed the covariances between dividend growth rates and 8, 12, and 16 quarter consumption growth rates. To control for the potential biases, we demean the one period growth rates of dividends and consumption, and measure the j period covariance as the average of the cross-product of the demeaned consumption and dividend growth rates using all $T - j$ data. We compute the long run cash flow beta using the Bartlett weighted (see Newey and West (1987)) K horizon covariances, and this long-run covariance measure is divided by the variance of the K period consumption growth. Our results based on this exercise are very similar to those reported above. In particular, over the 8, 12, and 16 quarter horizons, the estimated λ_c is 0.303, 0.265, and 0.175, respectively. The associated cross-sectional $\bar{R}^2$'s are 48%, 49%, and 37%, respectively. Collectively, this further corroborates our evidence. The covariance of dividend growth with long lags of consumption growth contains important information about risk premia across assets.

An additional robustness check that we conduct is to explore these relationships with an extension of our sample period to 1953. The data are available for the this longer sample for the quintile portfolios (15 in all) for the three sorts used in the paper. Our results are very similar to the more extensive quintile and decile portfolios reported and discussed for the post 1967 sample.

Jagannathan and Wang (1996) highlight the importance of time-varying market beta's for explaining risk premia. Similarly, Lettau and Ludvigson (2001) highlight the importance of time-varying consumption beta's in explaining the cross-section of risk premia. This paper highlights the importance of the link between consumption and dividends to explain the cross-section of risk premia, but we suspect that all these channels are important for interpreting differences in risk premia across assets.

5 Conclusion

The idea that differences in exposures to sources of systematic risk should justify differences in risk premia across assets is important to financial economics. We present a simple, parsimonious general equilibrium model, in which consumption betas directly mirror the exposure of dividends to consumption (cash flow beta's). We show that the measured consumption exposure of dividends does quite well in terms of explaining cross-sectional differences in the risk premia on 30 portfolios comprised of 10 size, 10 momentum, and 10 book-to-market portfolios. We measure the cash flow beta of a given dividend stream by measuring the covariance of dividend growth rates with long lags of consumption growth, and alternatively as stochastic cointegration parameter between dividends and consumption.

The cash flow beta model can account for more that 50% of the cross-sectional differences in risk premia across 30 assets, and the risk premium associated with the consumption risk is positive and highly significant. This performance compares very favorably against standard factor models. We find that the extreme loser and low book-to-market portfolio dividends have low cash flow beta's and low risk premia. In sharp contrast, the winner portfolio and the high book-to-market portfolio have large positive cash flow beta's and large positive risk premia. We document 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 size spread (small firm less large firm return). We also provide finite sample empirical distributions for the various key parameters, e.g. the price of consumption risk. Our finite sample distribution for the economic parameters of interest corroborates our evidence in the data.

Our overall empirical evidence suggests that dividend exposures to low frequency movements in consumption provide very valuable information regarding the cross-sectional differences in risk premia. Assets which have large exposures to this non-diversifiable source of risk also carry large risk premia.

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6 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

$$R_{i,t+1} = \frac{1 + \frac{P_{i,t+1}}{D_{i,t+1}}}{\frac{P_{i,t}}{D_{i,t}}} \frac{D_{i,t+1}}{D_{i,t}} \tag{23}$$

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 (23), which is expressed in log form as

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} z_{i,t+1} - z_{i,t} + g_{t+1} \tag{24}$$

where lowercase letters represent logs of their uppercase counterparts.[12] 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.

6.1 Equilibrium

All asset returns in this endowment economy must satisfy the standard asset pricing condition that

$$E_t[M_{t+1} R_{i,t+1}] = 1 \tag{26}$$

The log of the IMRS is labeled as m_{t+1}. The one step ahead innovation in the log of the IMRS is,

$$\eta_{M,t+1} = -\frac{\theta}{\psi}\eta_{t+1} - (1-\theta)\eta_{c,t+1} \tag{27}$$

where η_{t+1} is the innovation in log aggregate consumption growth and $\eta_{c,t+1}$ is the innovation in the log return $r_{c,t+1}$ (note, $r_{c,t+1} \equiv \ln(R_{c,t+1})$). Risk premia are determined by computing

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

$$\kappa_{i,1} = \frac{\exp(\bar{z}_i)}{1 + exp(\bar{z}_i)},\ \kappa_{i,0} = -\log(\kappa_{i,1}) - (1-\kappa_{i,1})\bar{z}_i \tag{25}$$

an asset's return covariance with the innovation in equation (27). It is well recognized that $r_{c,t+1}$ is endogenous to the model (see Cochrane and Hansen (1992), Campbell (2000)), 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.

To solve for the equilibrium, we conjecture that the log wealth consumption ratio, $z_{c,t}$, is linear in the state variable, x_t:

$$z_{c,t} = A_{c,0} + A_{c,1} x_t \tag{28}$$

Given our set-up Our the return on the portfolio that pays consumption and the IMRS are joint log-normally 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

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

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(1,1) process as follows:

$$\begin{aligned} c_{t+1} - c_t &= g_t = (1-\rho)\mu_c + \rho g_t + \eta_{t+1} - \omega \eta_t & (29) \\ x_{t+1} &= (1-\rho)\mu_x + \rho x_t + (\rho - \omega)\eta_{t+1} & (30) \end{aligned}$$

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

$$\begin{gathered} \theta \ln \delta - \tfrac{\theta}{\psi}((1-\rho)\mu_c + x_t + x_t) \\ +(\theta)[\kappa_{c,0} + \kappa_{c,1}\{A_{c,0} + A_{c,1}((1-\rho)\mu_x + \rho x_t)\} - A_{c,0} - A_{c,1}x_t + (1-\rho)\mu_c + x_t] \end{gathered} \tag{31}$$

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

$$-\frac{\theta}{\psi} + (\theta)[\kappa_{c,1} A_{c,1} \rho - A_{c,1} + 1] = 0 \tag{32}$$

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

$$A_{c,1} = \frac{1 - \frac{1}{\psi}}{1 - \kappa_{c,1}\rho} \tag{33}$$

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

$$r_{c,t+1} - E_t[r_{c,t+1}] = \eta_{c,t+1} = B_c \eta_{t+1} \tag{34}$$

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:

$$\eta_{M,t+1} = -\frac{\theta}{\psi}\eta_{t+1} - (1-\theta)\eta_{c,t+1} = -[-\frac{\theta}{\psi} - (1-\theta)B_c]\eta_{t+1} \equiv B_M \eta_{t+1} \tag{35}$$

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

$$E_t\left[r_{i,t+1} - r_{f,t}\right] = cov_t\left(-\eta_{M,t+1}, r_{i,t+1}\right) - var(r_{i,t+1})/2 \tag{36}$$

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

$$E_t\left[R_{i,t+1} - R_{f,t}\right] = \beta_i[B_M \sigma_\eta^2] \tag{37}$$

where the fundamental $\beta_i = \frac{cov(r_i,\eta)}{\sigma_\eta^2}$. Note that $B_M\sigma_\eta^2 = -[-\frac{\theta}{\psi} - (1-\theta)B_c]\sigma_\eta^2$, is the equilibrium market price of consumption risk.

6.2 Cash Flow Beta Model: Growth Rates

We 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:

$$d_{i,t+1} - d_{i,t} = g_{i,t+1} = \delta_i + \varphi_i x_t + \eta_{i,t+1} \tag{38}$$

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

$$z_{i,t} = A_{i,0} + A_{i,1}x_t \tag{39}$$

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:

$$-\frac{1}{\psi}+\varphi_i - A_{i,1}[1-\kappa_{i,1}\rho]=0 \tag{40}$$

The solution for the coefficient is given by

$$A_{i,1}=\frac{\varphi_i-\frac{1}{\psi}}{1-\kappa_{i,1}\rho} \tag{41}$$

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

$$E_t\left[R_{i,t+1}-R_{f,t}\right]=\beta_i[B_M\sigma_\eta^2] \tag{42}$$

Since the return innovation is

$$r_{i,t+1}-E_t[r_{i,t+1}]=[\tau_i+\kappa_{i,1}A_{i,1}(\rho-\omega)]\eta_{t+1}+\eta_{i,t+1}, \tag{43}$$

it follows that the consumption beta of the asset

$$\beta_i=\tau_i+\kappa_{i,1}A_{i,1}(\rho-\omega) \tag{44}$$

6.3 Cash Flow Beta Model: Cointegration

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

$$z_{i,t}=A_{i,0}+A_{i,1}x_t+A_{i,2}\epsilon_{i,t} \tag{45}$$

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:

$$d_{i,t+1}=\mu_i+\delta_i\cdot(t+1)+\phi_i c_{t+1}+\epsilon_{i,t+1} \tag{46}$$

Taking the first difference, and substituting for the assumed consumption growth rate process (4), it follows that

$$g_{i,t+1} = \delta_i + \phi_i x_t + \phi_i \eta_{t+1} + \epsilon_{i,t+1} - \epsilon_{i,t} \tag{47}$$

where we assume

$$\epsilon_{i,t+1} = \xi_i \epsilon_{i,t} + u_{i,t+1} \tag{48}$$

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,

$$-\frac{1}{\psi} + \phi_i - A_{i,1}[1 - \kappa_{i,1}\rho] = 0 \tag{49}$$

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

$$\kappa_{i,1} A_{i,2} \xi_i - A_{i,2} + \xi_i - 1 = 0 \tag{50}$$

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

$$A_{i,1} = \frac{\phi_i - \frac{1}{\psi}}{1 - \kappa_{i,1}\rho} \quad A_{i,2} = \frac{\xi_i - 1}{1 - \kappa_{i,1}\xi_i} \tag{51}$$

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

$$E_t\left[R_{i,t+1} - R_{f,t}\right] = \beta_i [B_M \sigma_\eta^2] \tag{52}$$

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

$$r_{i,t+1} - E_t[r_{i,t+1}] = [\phi_i + \kappa_{i,1} A_{i,1}(\rho - \omega)]\eta_{t+1} + (1 + \kappa_{i,1} A_{i,2}) u_{i,t+1} \tag{53}$$

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

$$\beta_i = \phi_i + \kappa_{i,1} A_{i,1}(\rho - \omega) \tag{54}$$

6.4 GMM Estimation

Let the true parameter vector be given by:

$$\Psi_0 = \left[\begin{array}{cccccccc} \alpha_1 & \cdots & \alpha_N & \beta_1' & \cdots & \beta_N' & \lambda_0 & \lambda' \end{array} \right] \tag{55}$$

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

$$R_{i,t+1} - R_{f,t} = \alpha_i + \beta_i' \mathbf{f}_{t+1} + e_{i,t+1} \tag{56}$$

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):

$$\begin{aligned} E[e_{i,t+1}] \quad &= 0 \ \forall i = 1, \ldots, N \\ E[e_{i,t+1}\mathbf{f}_{t+1}] \quad &= 0 \ \forall i = 1, \ldots, N \end{aligned} \tag{57}$$

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:

$$E[R_{i,t+1} - \lambda_0 - \beta_i' \lambda] = 0 \ \forall i = 1, \ldots, N \tag{58}$$

We can stack the sample counterparts to the moment conditions (57) and (58) as follows (Hansen (1982)):

$$g_T(\Psi) = \frac{1}{T} \sum_{t=1}^{T} f(X_t, \Psi) \tag{59}$$

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

$$A_T' g_T = 0 \tag{60}$$

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.

$$A_T = \begin{bmatrix} I_{N(K+1)} & 0_{N(K+1)\times 1} & 0_{N(K+1)\times 1} & \cdots & 0_{N(K+1)\times 1} \\ 0_{N,N} & 1_{N\times 1} & \hat{\beta}_1 & \cdots & \hat{\beta}_K \end{bmatrix} \tag{61}$$

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

$$\sqrt{T}(\Psi_T - \Psi_0) \sim N(0, (AD)^{-1}(ASA')(AD)^{-1\prime}) \tag{62}$$

where D is the gradient of the stacked moment conditions in equation (59), and S is the variance-covariance matrix of the moment conditions, for which the sample counterpart is estimated using Newey and West (1987) with 4 lags. Using larger number of lags makes no significant difference to our results. The standard errors on the cointegration parameters ϕ_i, were constructed using 8 Newey-West lags. Additional lags make no material difference.

Table 1: **Cross-Sectional Evidence: 15 Portfolios**

Panel A: Summary Statistics

	Returns		Dividend Growth		Cash Flow Beta's			
Portfolio	Mean	Std.	Mean	Std.	φ_i	S.E.	ϕ_i	S.E.
M1-2	0.48	13.01	-1.57	13.15	-2.65	5.50	-5.37	3.34
M3-4	1.65	9.81	-0.32	7.09	-0.79	3.93	-5.09	2.17
M5-6	1.71	8.45	0.15	6.30	2.03	2.30	-0.88	0.97
M7-8	2.42	8.21	0.93	7.85	5.78	3.79	0.08	1.70
M9-10	3.42	9.98	1.84	11.67	9.33	5.71	10.18	3.65
S1-2	2.47	13.12	0.37	4.20	1.87	2.25	0.37	2.36
S3-4	2.59	11.87	0.30	3.34	1.05	1.48	1.94	1.51
S5-6	2.54	10.76	0.35	2.97	2.00	1.30	1.14	1.63
S7-8	2.41	10.01	0.32	4.68	0.82	1.31	0.32	1.79
S9-10	2.21	8.11	0.13	1.60	1.34	0.55	-0.89	1.25
B1-2	2.15	9.93	0.19	3.68	-0.83	1.82	-1.11	1.45
B3-4	2.21	9.04	0.28	5.85	-0.23	2.41	-0.78	2.07
B5-6	2.18	7.85	0.16	2.83	0.60	1.19	-2.31	1.36
B7-8	2.53	8.21	0.55	2.84	2.07	1.22	3.59	1.11
B9-10	3.06	9.25	1.05	4.82	5.58	2.88	1.47	3.48

Panel B: Unconditional Models

Model	λ_0	λ_c	R^2
Cash Flow beta	1.947	0.172	0.584
	(0.210)	(0.049)	
Cash Flow beta(coint)	2.232	0.152	0.684
	(0.097)	(0.027)	

Panel A of Table 1 presents descriptive statistics (in percentages) for the 15 characteristic sorted quintile portfolios. Value-weighted returns and log dividend growth rates are presented for portfolios formed on momentum (M), market capitalization (S), and book-to-market ratio (B). M1-2 represents the lowest momentum (loser) quintile, S1-2 the lowest size (small firms) quintile, and B1-2 the lowest book-to-market quintile. In the column labeled "Cash Flow Beta," the relevant measure, φ_i, is retrieved by performing the following regression:

$$g_{i,t+1} = \delta_i + \varphi_i x_t + \epsilon_{i,t+1}$$

where $g_{i,t}$ denotes the cash flow growth rate for portfolio i at time t, and x_t denotes a two-year smoothed growth rate of real per capita consumption of nondurables and services at time t. To measure the cash flow beta parameter ϕ_i via stochastic cointegration we first detrend the log consumption and dividend series by regressing the log level of consumption and dividends on a constant and a time trend. The resulting de-trended time series, c_t^* and d_t^*, are then used to measure ϕ_i. More specifically, we follow Stock and Watson (1993) and use dynamic least squares to estimate ϕ_i; that is we estimate ϕ_i via

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

with $K = 4$. Robust standard errors are provided in the columns next to the parameter estimates. Data are converted to real using the PCE deflator. The data are sampled at the quarterly frequency, and cover the 3rd quarter 1967 through 4th quarter 1999. Panel B presents estimated risk premia and standard errors obtained from one-step GMM estimation of the risk measures and the consumption risk premium as discussed in the appendix. Risk prices are expressed in quarterly percentage terms.

Table 2: **Summary Statistics**

	Returns		Dividend Growth	
Portfolio	Mean	Std.	Mean	Std.
M1	-0.63	15.48	-2.84	20.35
M2	0.90	12.09	-1.14	12.09
M3	1.29	10.57	-0.73	10.48
M4	1.91	9.50	0.01	7.75
M5	1.59	8.62	0.05	8.56
M6	1.81	8.61	0.25	8.36
M7	2.27	8.63	0.76	9.70
M8	2.58	8.22	1.08	9.77
M9	3.18	9.38	1.83	11.73
M10	3.83	11.38	2.12	17.21
S1	2.46	13.53	0.49	5.73
S2	2.49	12.82	0.24	3.89
S3	2.62	12.07	0.29	4.96
S4	2.56	11.76	0.30	4.09
S5	2.76	11.13	0.52	5.21
S6	2.36	10.54	0.21	2.76
S7	2.48	10.43	0.47	3.70
S8	2.35	9.81	0.20	6.73
S9	2.21	8.97	0.19	4.10
S10	2.21	8.01	0.09	1.69
B1	2.00	10.53	0.15	4.49
B2	2.31	9.50	0.29	5.46
B3	2.37	9.31	0.47	8.03
B4	2.12	9.08	0.17	6.75
B5	1.98	7.96	-0.01	4.38
B6	2.43	8.09	0.40	3.00
B7	2.46	8.37	0.43	3.45
B8	2.62	8.41	0.64	3.82
B9	2.99	8.88	1.08	4.12
B10	3.19	10.49	1.00	8.60

Table 2 presents descriptive statistics (in percentages) for the 30 characteristic sorted decile portfolios. Value-weighted returns and log dividend growth rates are presented for portfolios formed on momentum (M), market capitalization (S), and book-to-market ratio (B). M1 represents the lowest momentum (loser) decile, S1 the lowest size (small firms) decile, and B1 the lowest book-to-market decile. Data are converted to real using the PCE deflator. The data are sampled at the quarterly frequency, and cover the 3rd quarter 1967 through 4th quarter 1999.

Table 3: **Cross-Sectional Evidence: 30 Portfolios**

Model	λ_0	λ_c	λ_g	λ_{vw}	λ_{SMB}	λ_{HML}	$\bar{R}^2$
Cash Flow Beta	1.908	0.167					0.510
	(0.231)	(0.053)					
Cash Flow Beta(Coint)	2.207	0.141					0.574
	(0.101)	(0.032)					
CCAPM	1.564		0.212				0.046
	(0.383)		(0.074)				
CAPM	3.548			-1.221			0.030
	(1.620)			(1.673)			
3-Factor	9.060			-6.694	0.004	-0.128	0.243
	(3.237)			(3.286)	(0.251)	(0.883)	

Table 3 presents results for cross-sectional regressions, utilizing a set of 30 portfolios (10 size, 10 momentum, and 10 book-to-market). Parameter estimates and robust standard errors are obtained in a single step via GMM as discussed in the appendix. The factors utilized in the analysis are: 1) The 2-year smoothed growth rate of log real per capita consumption of nondurables and services, c, 2) Log rate of change in real 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, and $\bar{R}^2$ represents the regression R^2 adjusted for degrees of freedom. Risk prices are expressed in quarterly percentage terms. The data cover the period 1967.3-1999.4, and are converted to real using the PCE deflator.

Table 4: **Smoothed Growth Rate Risk Measures**

Portfolio	Quarter:1	4	8
M1	-2.83	-3.97	-4.04
M2	2.91	1.59	-1.68
M3	1.58	0.34	-0.85
M4	1.58	-0.66	-0.25
M5	3.23	3.99	0.41
M6	0.62	0.72	3.32
M7	1.25	4.51	5.14
M8	-3.84	0.88	6.57
M9	-2.33	6.17	8.86
M10	-1.63	4.66	10.80
S1	2.18	3.25	1.57
S2	1.58	3.14	2.98
S3	0.93	2.57	0.89
S4	0.74	1.43	1.44
S5	-0.01	1.99	1.54
S6	1.30	2.53	2.33
S7	0.63	1.74	1.72
S8	0.06	-0.90	0.27
S9	0.34	1.97	1.03
S10	0.29	1.08	1.40
B1	1.30	2.40	4.00
B2	-1.34	-3.50	-3.54
B3	0.43	2.65	0.38
B4	-0.38	-1.40	-1.16
B5	-1.45	-1.23	-0.31
B6	-0.30	0.29	1.78
B7	-0.89	-0.23	0.96
B8	1.78	4.13	3.69
B9	0.79	3.95	5.15
B10	1.87	6.45	8.04

Panel B1: One Quarter			Panel B2: Four Quarters		
λ_0	λ_c	$\bar{R}^2$	λ_0	λ_c	$\bar{R}^2$
2.264	-0.022	-0.033	1.940	0.188	0.341
(0.238)	(0.127)		(0.259)	(0.078)	

Table 4 presents risk measures and results for cross-sectional regressions, utilizing a set of 30 decile portfolios (10 momentum (M), 10 size (S), and 10 book-to-market (B)). M1 represents the lowest momentum (loser) decile, S1 the lowest size (small firms) decile, and B1 the lowest book-to-market decile. Parameter estimates and robust standard errors are obtained from a one-step GMM regression as discussed in the appendix. The factor utilized in the analysis is the log rate of change in real per capita consumption, g. Cash flow growth rates are regressed on one-quarter consumption growth (Panel B1), smoothed 4 quarters consumption growth (Panel B2), and smoothed 8 quarters consumption growth (as in Table 3). $\bar{R}^2$ represents the regression R^2 adjusted for degrees of freedom. Risk prices are expressed in quarterly percentage terms. The data cover the period 1967.3-1999.4, and are converted to real using the PCE deflator.

Table 5: Monte Carlo: Alternative Distribution

Panel A: Time Series

	Risk Measure (φ)						R^2(%)					
	φ_0	2.5%	10%	50%	90%	97.5%	R_0^2	50.0%	60.0%	70.0%	80.0%	90.0%
m1	**0.000**	-25.779	-16.058	0.299	15.941	25.190	**0.0**	0.3	0.5	0.8	1.2	2.0
m5	**0.000**	-10.926	-6.773	0.020	6.843	11.008	**0.0**	0.4	0.6	0.8	1.3	2.1
m10	**0.000**	-21.636	-14.073	-0.099	13.869	21.620	**0.0**	0.4	0.6	0.9	1.3	2.1
s1	**0.000**	-11.093	-7.306	-0.047	7.336	11.046	**0.0**	0.9	1.4	2.2	3.3	5.3
s5	**0.000**	-8.309	-5.438	-0.069	5.262	8.074	**0.0**	0.6	0.9	1.4	2.1	3.4
s10	**0.000**	-3.016	-2.036	0.000	1.981	2.956	**0.0**	0.8	1.3	1.9	2.9	4.6
b1	**0.000**	-9.168	-6.077	0.065	6.149	9.364	**0.0**	1.1	1.7	2.6	3.7	5.9
b5	**0.000**	-6.469	-4.174	-0.041	4.022	6.327	**0.0**	0.5	0.8	1.2	1.8	2.9
b10	**0.000**	-16.276	-10.841	-0.200	10.648	16.051	**0.0**	0.9	1.4	2.1	3.2	5.1

Panel B: Cross Section

Risk Price ($\lambda_c \times 100$)						R^2(%)									
$\lambda_{c,0}$	2.50%	10%	50%	90%	97.50%	$\bar{R}_{cs}^2$	10%	20%	30%	40%	50%	60%	70%	80%	90%
0.000	-0.127	-0.097	-0.003	0.096	0.124	**0.0**	-0.8	1.8	5.7	11.2	18.9	26.2	34.5	43.8	55.1

Table 5 presents the simulated distribution of prices of risk, adjusted R^2, and risk measures for the cash flow beta model examined in the paper under the alternative distribution. Simulations are conducted as follows. 10,000 sample paths of 130 quarterly observations of consumption growth are generated via an i.i.d. process for consumption growth:

$$\hat{g}_{t+1} = \mu + \eta_{t+1}$$

with quarterly $\mu = 0.0052$ and annualized $\sigma_\eta^2 = 0.0090$. We project the observed dividend growth rates on a trailing eight quarter moving average of the simulated consumption growth:

$$d_{i,t+1} - d_{i,t} = \mu_i + \hat{\varphi}_i \hat{x}_t + \eta_{i,t+1}$$

and regress the observed mean returns on the cross section of retrieved projection coefficients:

$$\bar{r}_i = \lambda_0 + \lambda_c \hat{\varphi}_i + u_i$$

Parameters are estimated in a single step via GMM. We present percentile breakpoints for the distribution of estimated φ, λ_c, $\bar{R}_{cs}^2$ for the cross-sectional regression, and R^2 for the time series regression of dividend growth rates on simulated consumption growth.

Table 6: Monte Carlo: Null Distribution

Panel A: Time Series

	Risk Measure (φ)						R^2(%)
	φ_0	2.5%	10%	50%	90%	97.5%	R^2_0
m1	**-4.04**	-19.75	-14.10	-4.06	5.70	12.84	**0.01**
m5	**0.41**	-6.61	-3.83	0.26	4.60	7.20	**0.03**
m10	**10.80**	-2.61	2.35	10.61	18.85	24.18	**0.90**
s1	**1.57**	-2.99	-1.38	1.54	4.33	6.09	**1.90**
s5	**1.54**	-2.22	-0.94	1.53	3.90	5.48	**2.19**
s10	**1.40**	0.01	0.57	1.42	2.20	2.73	**2.45**
b1	**4.00**	0.17	1.69	4.09	6.28	7.53	**2.30**
b5	**-0.31**	-3.88	-2.63	-0.28	1.91	3.01	**0.01**
b10	**8.04**	0.61	3.64	8.08	12.49	14.88	**8.11**

Panel B: Cross Section

Price of Risk ($\lambda_c \times 100$)						R^2(%)									
$\lambda_{c,0}$	2.50%	10%	50%	90%	97.50%	$\bar{R}^2_{cs}$	10%	20%	30%	40%	50%	60%	70%	80%	90%
0.167	0.094	0.100	0.106	0.114	0.125	**100.0**	26.7	39.9	48.4	54.6	59.4	63.2	67.4	71.6	77.8

Table 6 presents the simulated distribution of prices of risk, adjusted R^2, and risk measures for the cash flow beta model examined in the paper under the null distribution. Simulations are conducted as follows. 10,000 sample paths of 130 quarterly observations of consumption growth are generated via an ARMA (1,1)process for consumption growth:

$$g_{t+1} = \mu + \rho x_t + (\rho - \omega)\eta_{t+1}$$

with quarterly $\rho = 0.730$, $\omega = 0.404$, $\mu = 0.0052$ and annualized $\sigma_\eta = 0.0082$. Portfolio dividend growth is generated as:

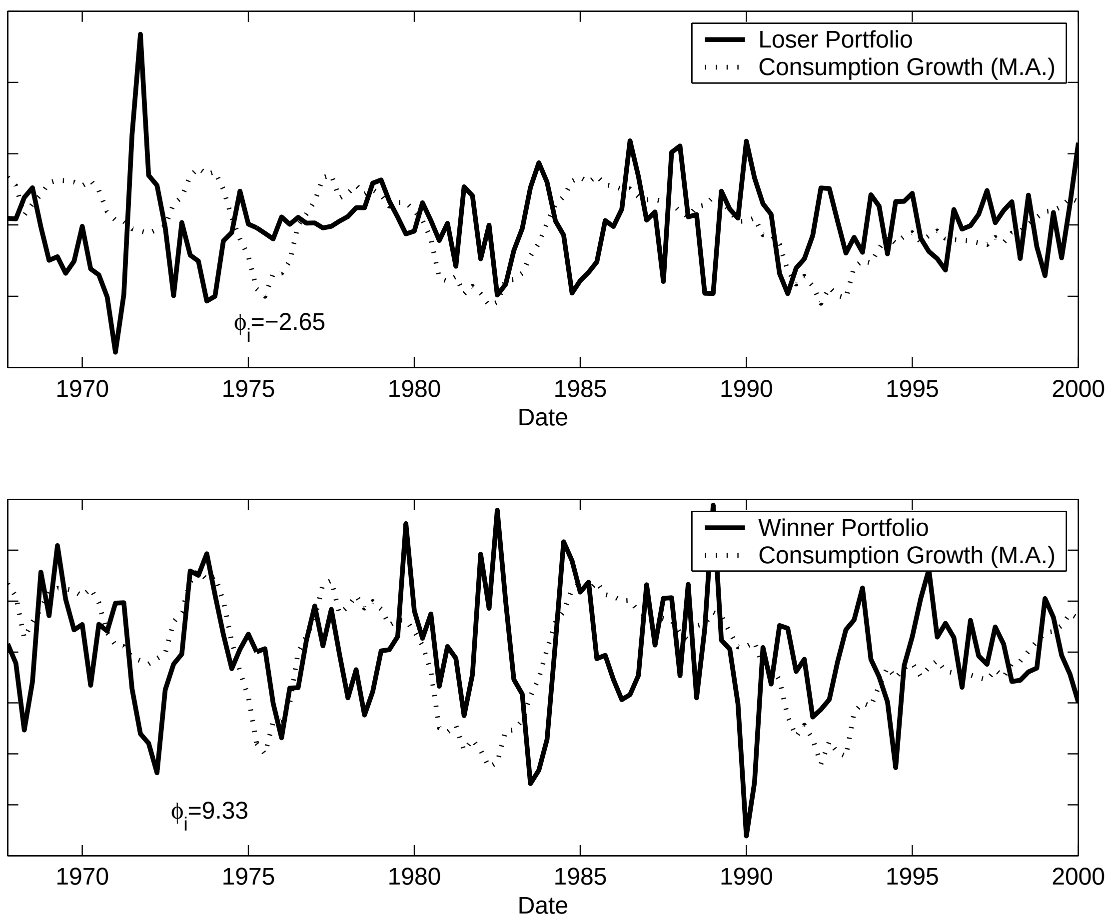
$$\hat{d}_{i,t+1} - \hat{d}_{i,t} = \mu_i + \varphi_{0,i}\tilde{x}_t + \eta_{i,t+1}$$

where $\tilde{x}_t$ represents a trailing eight quarter moving average of the simulated consumption growth series. The mean dividend growth rate and the covariance matrix of the residuals, η are chosen to match the mean and covariance matrix of the dividend growth rates observed in the data. We then project generated dividend growth rates onto the simulated trailing eight quarter moving average of consumption growth and retrieve the estimated $\hat{\varphi}_i$. Returns are constructed using equations (42) and (43), with preference parameters chosen to match $\lambda_c = 0.167$. We regress the mean returns on the cross section of retrieved projection coefficients:

$$\bar{r}_i = \lambda_0 + \lambda_c \hat{\varphi}_i + u_i$$

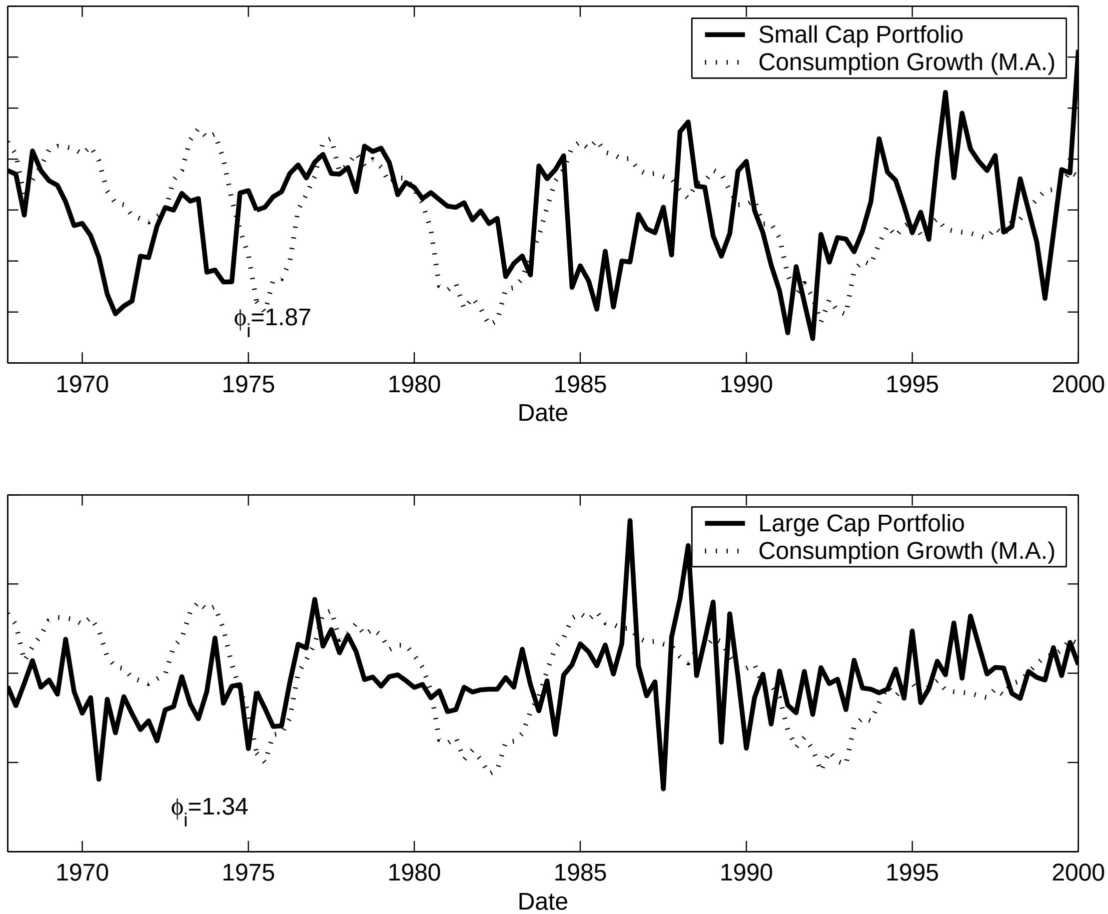
We present percentile breakpoints for the distribution of estimated φ, λ_c, $\bar{R}^2_{cs}$ for the cross-sectional regression, and R^2 for the time series regression of dividend growth rates on simulated consumption growth. Parameters are estimated in a single step via GMM.

Figure 1: **Momentum Portfolios**



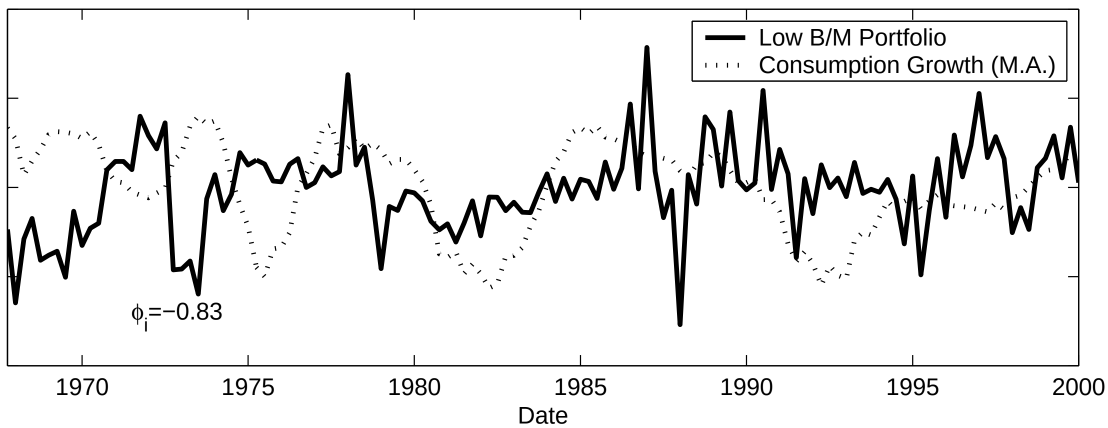
The figure presents the dividend growth series for the top and bottom momentum quintile portfolios, as well as the trailing eight quarter moving average of consumption growth. φ_i refers to the regression slope coefficient from regressing the dividend growth rate series on the trailing eight quarter moving average of consumption growth.

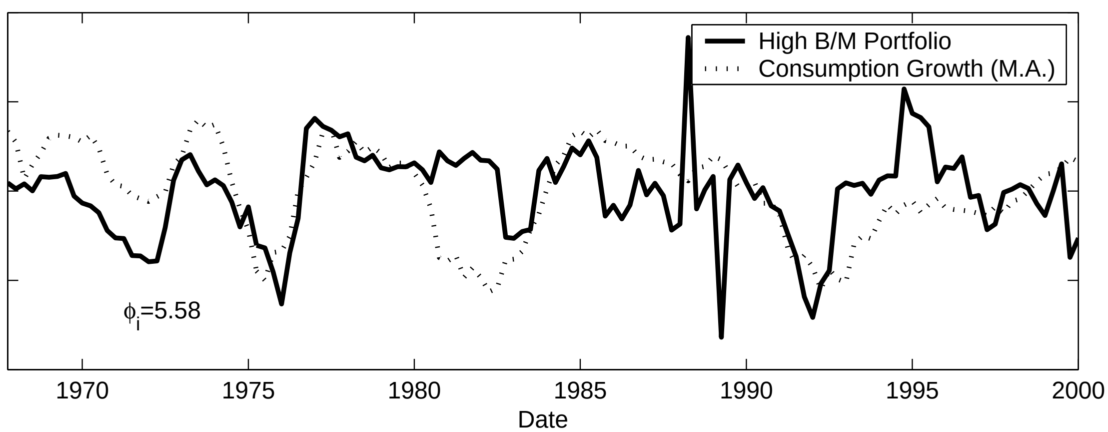
Figure 2: **Capitalization Portfolios**



The figure presents the dividend growth series for the top and bottom capitalization quintile portfolios, as well as the trailing eight quarter moving average of consumption growth. φ_i refers to the regression slope coefficient from regressing the dividend growth rate series on the trailing eight quarter moving average of consumption growth.

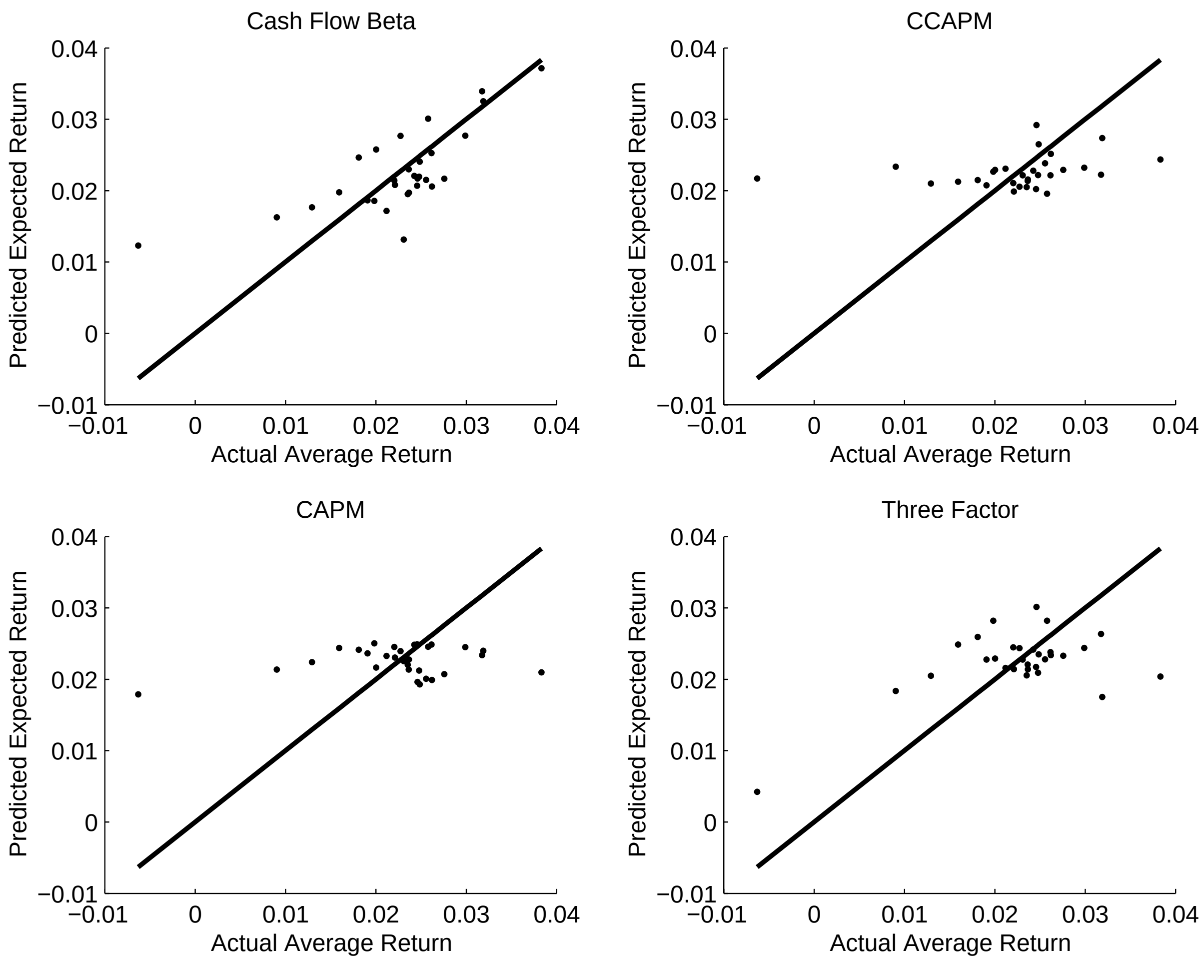
Figure 3: **Book-to-Market Portfolios**





The figure presents the dividend growth series for the top and bottom book-to-market quintile portfolios, as well as the trailing eight quarter moving average of consumption growth. φ_i refers to the regression slope coefficient from regressing the dividend growth rate series on the trailing eight quarter moving average of consumption growth.

Figure 4: **Scatterplots: Unconditional Models**



The figure presents scatterplots for the unconditional models estimated in the paper. The fitted expected returns are plotted against mean realized returns.