Consumption, Dividends, and the Cross Section of Equity Returns

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ABSTRACT

We show that aggregate consumption risks embodied in cash flows can account for the puzzling differences in risk premia across book-to-market, momentum, and size-sorted portfolios. The dynamics of aggregate consumption and cash flow growth rates, modeled as a vector autoregression, are used to measure the consumption beta of discounted cash flows. Differences in these cash flow betas account for more than 60% of the cross-sectional variation in risk premia. The market price for risk in cash flows is highly significant. We argue that cash flow risk is important for interpreting differences in risk compensation across assets.

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 (capital asset-pricing model) (see Sharpe (1964) and 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) 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 observable rates of return across assets. Consequently, identifying economic sources of risks that justify differences in the measured risk premia continues to be an important economic issue.

Asset prices reflect the discounted value of cash flows; return news, consequently, reflects revisions in expectations about the entire path of future

cash flows and discount rates. Changes in expectations of cash flows is an important ingredient determining asset return news. Systematic risks in cash flows therefore should have some bearing on the risk compensation of assets. In particular, assets whose cash flows have higher aggregate consumption risks (i.e., larger cash flow beta) should also carry a higher risk premium. This intuition is also captured in the consumption-based models presented in Abel (1999) and Bansal and Yaron (2004), who show that differences in risk compensation on assets mirror differences in the exposure of assets' cash flows to consumption. Motivated by these common implications, we explore whether the dynamic relation between two quantities, cash flows and aggregate consumption, has any bearing on the observed cross-sectional differences in expected returns.

An important dimension of this paper is the measurement of cash flow betas. We model the joint dynamics of observed cash flow and aggregate consumption growth rates as a vector autoregression (VAR). This VAR is used to measure cash flow news—the revision in expectations of the discounted sum of future cash flow growth rates (see equation (3)). The projection coefficient of this cash flow news onto the current consumption innovation is the asset's cash flow beta.

Using data on consumption and dividends, we directly measure cash flow betas for 30 equity 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 62% 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 (winner minus loser), size (small capitalization minus large), and value (high book-to-market minus low) portfolios.

While cash flow betas contain very valuable information about the differences in risk premia, the standard consumption beta, as documented in earlier papers, does not. In models that rely on Epstein and Zin (1989) preferences (e.g., Bansal and Yaron (2003)), the consumption beta may not be sufficient to measure the risk of an asset. The cash flow betas and the standard consumption betas differ and do not provide the same information about risk premia. Consequently, the ability of the cash flow and consumption betas to explain differences in mean returns can be quite different. We elaborate on this intuition to interpret our empirical findings.

We focus on size, book-to-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 specification, the static CAPM, and the C-CAPM. Our empirical work estimates the time-series cash flow betas 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 betas developed in the paper can capture approximately 62% of the cross-sectional variation in risk premia. The price of consumption risk in cash flows, the slope coefficient on the cash flow betas in the cross-section of assets, is highly statistically significant. The point estimate is about 0.12% (SE = 0.03). Further, betas associated with benchmark factor models cannot explain the cross-sectional variation in risk premia, and in many cases, the premium associated with the risk factor is negative. To evaluate our empirical evidence, we also conduct two Monte Carlo experiments: 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 corroborates our empirical evidence.

Earlier work by Jagannathan and Wang (1996) highlights the importance of time-varying betas in capturing risk premia. Lettau and Ludvigson (2001) highlight the importance of time-varying consumption betas, and consequently discount rates, in explaining risk premia. By focusing on the cash flow exposures to consumption risks, our evidence complements these findings. Economic risks in cash flows, an important ingredient determining asset returns, provide very valuable information about systematic risks in asset returns.

Section I provides the relationship between the cash flow and return consumption betas. Section II provides a data description. Section III details the empirical evidence pertaining to the estimation of the cash flow betas and the ability of the cash flow betas to explain cross-sectional variation in risk premia. Section III also provides Monte Carlo evidence and several important robustness checks. Finally, Section IV concludes.

I. Asset Returns and Cash Flow Betas

In the following section we provide the relation between return innovations, cash flow news, and discount rate news. We use this relation to highlight that cash flow news is an important ingredient governing return news, hence, any systematic risks in cash flows should have a bearing on the risk premium for the asset.

A. *Return Decomposition*

For any asset i, consider the Campbell and Shiller (1988) linear approximation for the log return, $r_{i,t} = \ln(1 + R_{i,t}) = \ln(P_{i,t} + D_{i,t}) - \ln(P_{i,t-1})$:

$$r_{i,t} \approx \kappa_{i,0} + g_{i,t} + \kappa_{i,1}pd_{i,t} - pd_{i,t-1}, \tag{1}$$

where $pd_{i,t} = \ln(P_{i,t}/D_{i,t})$ is the log price–cash flow ratio, $g_{i,t}$ the log cash flow growth rate, and r_i, the log return. The parameters $\kappa_{i,0}$ and $\kappa_{i,1}$ are parameters

in the linearization; $\kappa_{i,1}$ is strictly less than 1.[1] At this point, we interpret the cash flow, $D_{i,t}$, as the general payout to which the equity holder has claim.

Using (1), the log price–cash flow ratio, assuming that the usual transversality condition holds is

$$pd_{i,t} = \frac{\kappa_{i,0}}{(1 - \kappa_{i,1})} + E_t\left[\sum_{j=0}^{\infty}\kappa_{i,1}^j g_{i,t+1+j} - \sum_{j=0}^{\infty}\kappa_{i,1}^j r_{i,t+1+j}\right]. \qquad (2)$$

The log price–cash flow ratio is determined by the time path of expected cash flow growth rates and expected returns.

As in Campbell (1996), return innovations are related to innovations in expectations of future cash flows and returns. Specifically, taking expectations of (1) and (2) and rearranging, we obtain

$$r_{i,t} - E_{t-1}[r_{i,t}] = \{E_t - E_{t-1}\}\left[\sum_{j=0}^{\infty}\kappa_{i,1}^j g_{i,t+j}\right]$$

$$- \{E_t - E_{t-1}\}\left[\sum_{j=1}^{\infty}\kappa_{i,1}^j r_{i,t+j}\right] = \eta_{g_i,t} - \eta_{e_i,t}, \qquad (3)$$

where $\eta_{g_i,t} = \{E_t - E_{t-1}\}[\sum_{j=0}^{\infty}\kappa_{i,1}^j g_{i,t+j}]$ represents the revision in expectations of the constant discounted (by $\kappa_{i,1}$) sum of future dividend growth rates. We refer to this quantity as cash flow news. Analogously, $\eta_{e_i,t}$ represents news regarding future expected returns. We refer to this as the discount rate news.

In models of asset pricing, expected returns are determined by the exposure of the return innovation to a source of priced risk. In the consumption CAPM (C-CAPM) (Breeden (1979)), risk is measured by the consumption beta—the slope coefficient from regressing return innovation onto the consumption innovation. Given the return decomposition above, the consumption beta can be described as

$$\beta_i = \frac{\text{Cov}(r_{i,t} - E_{t-1}[r_{i,t}], \eta_{c,t})}{\text{Var}(\eta_{c,t})} = \frac{\text{Cov}(\eta_{g_i,t} - \eta_{e_i,t}, \eta_{c,t})}{\text{Var}(\eta_{c,t})} = \beta_{i,g} - \beta_{i,e}, \qquad (4)$$

where $\eta_{c,t}$ is the time-t innovation in consumption growth. The consumption beta is governed by two components: the exposure of cash flow news and that of discount rate news to consumption innovations.

In this paper, we ask whether economic risks (measured as aggregate consumption risks) in cash flows have any bearing on the cross section of expected returns. That is, we focus on $\beta_{i,g}$ and explore whether this risk measure can capture differences in risk premia across assets. From equation (3), it is evident

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[1] More specifically, $\kappa_{i,1}$ is

$$\kappa_{i,1} = \frac{\exp(\bar{pd}_i)}{1 + \exp(\bar{pd}_i)},$$

and $\bar{pd}_i$ is the time-series average of the $pd_{i,t}$.

that cash flow news is an important ingredient governing return news. Economic risks embodied in cash flows therefore should have a bearing on the risk premia of assets. Assets with greater cash flow exposure to consumption risks should offer higher risk compensation. Further, a wide range of consumption-based models, where the discount rate is largely constant, also suggest that this should be the case; $\beta_{i,e}$, in this case is essentially zero, and the cash flow beta then would govern the consumption risk of the asset.

To interpret the implications of our empirical work, it is useful to consider the following simple factor structure for returns,

$$\mathbf{r}_t - \mathbf{E}_{t-1}(\mathbf{r}_t) = \mathbf{B}_c \eta_{c,t} - \mathbf{B}_e \eta_{e,t} + \epsilon_t. \tag{5}$$

Consistent with equation (4), the N vector of asset return news, $\mathbf{r}_t - \mathbf{E}_{t-1}(\mathbf{r}_t)$, has a factor structure. The two systematic risk factors, $\eta_{c,t}$ and $\eta_{e,t}$ are potentially correlated, and represent news in consumption growth and discount rates, respectively.[2] A typical element of the N vector $\mathbf{B}_c$ is the cash flow beta, $\beta_{i,g}$. Similarly, a typical element of $\mathbf{B}_e$ determines the exposure of asset returns to discount rate news. The N vector ϵ_t corresponds to the nonsystematic noise in asset return news.

Consumption-based models discussed in Kandel and Stambaugh (1991) and Bansal and Yaron (2003) lead to the factor structure in equation (5). Further, in these consumption-based models the standard consumption beta (as in Breeden (1979)) is not sufficient to explain differences in risk premia across assets; time-varying consumption volatility leads to varying discount rates, and additional state variables (e.g., consumption volatility) are priced as well. The magnitude of risk compensation in this model for the two priced sources of risk can be different.

Our empirical work answers two questions: (1) Do assets with cash flows with a larger aggregate consumption risk exposure (i.e., larger $\beta_{i,g}$) also have larger risk premia? (2) Does the relation between two quantities, cash flows and aggregate consumption, have any bearing on expected asset returns? Even if $\mathbf{B}_e$ is not zero, it is still the case that cash flows are an important ingredient determining asset returns, and greater systematic risk in cash flows should be compensated with higher expected returns. In Section III.D.3, we exploit the factor structure in equation (5) to explain why the standard return consumption beta may fail to account for the risk premia, while the cash flow beta may still account for a significant portion of the cross-sectional variation in risk premia.

B. Consumption and Cash Flow Dynamics

In this section we provide the details for estimating the cash flow's consumption beta. Demeaned log consumption growth, $g_{c,t}$, is assumed to follow a simple AR(1) process:

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[2] Extending equation (5) to a more general multiple factor framework, that is more than two factors, is straightforward.

$$g_{c,t} = \rho_c g_{c,t-1} + \eta_{c,t}. \tag{6}$$

For notational simplicity, all growth rates have been demeaned at the outset and have an unconditional mean of zero. As discussed above, the implication of expression (4) is that assets' risk premia are determined by the covariation of innovations in current and expected future cash flows with $\eta_{c,t}$, the innovation in consumption. In order to measure this covariance, we model an asset's cash flow growth dynamics as a function of aggregate consumption growth.

Specifically, we assume that the relationship between demeaned dividend and consumption growth rates is

$$g_{i,t} = \gamma_i \left(\frac{1}{K} \sum_{k=1}^{K} g_{c,t-k} \right) + u_{i,t} \tag{7}$$

$$u_{i,t} = \sum_{j=1}^{L} \rho_{j,i} u_{i,t-j} + \zeta_{i,t}. \tag{8}$$

The expression $\frac{1}{K} \sum_{k=1}^{K} g_{c,t-k}$ represents a trailing K-period moving average of past consumption growth. The parameter γ_i measures the covariance between cash flow growth and the history of consumption growth. Additionally, the specification allows for cash flow growth rates to depend on the current consumption innovation through $\zeta_{i,t}$. This dependence will be reflected in the measured covariances.

We characterize equations (6)–(8) as a simple VAR. The q-vector, z_t, is

$$z_t = [g_{i,t} u_{i,t} \cdots u_{i,t-(L-1)} g_{c,t} \cdots g_{c,t-(K-1)}]'. \tag{9}$$

The dynamics of the state variables and portfolio cash flow growth can then be expressed as

$$z_t = A z_{t-1} + v_t, \tag{10}$$

where A is the $q \times q$ matrix of coefficients. Further, let the first element of z_t be $g_{i,t}$ such that $e_1' z_t = g_{i,t}$, where e_1 is a $\times 1$ vector with first element 1 and remaining elements 0. From equation (3), it follows that $\eta_{g_i,t}$ is equal to

$$\eta_{g_i,t} = \{E_t - E_{t-1}\} \left[\sum_{j=0}^{\infty} \kappa_{i,1}^j g_{i,t+j} \right]$$

$$= e_1' \left[\sum_{j=0}^{\infty} \kappa_{i,1}^j A^j v_t \right]$$

$$= e_1' [I - \kappa_{i,1} A]^{-1} v_t. \tag{11}$$

This residual represents the innovation to current and expected future cash flow growth rates. We measure the exposure of this innovation to consumption

growth by projection on the innovation in consumption growth from expression (6),

$$\eta_{g_i,t} = \beta_{i,g}\eta_{c,t} + \xi_{g_i,t}. \tag{12}$$

We term the resulting coefficient, $\beta_{i,g}$, the asset's cash flow beta. Note that if $u_{i,t}$ is uncorrelated with consumption innovation, then the cross-sectional differences in the cash flow beta based on equation (12) reflect differences in γ_i. Hence, if one imposes the restriction that $u_{i,t}$ is uncorrelated with consumption innovations, then it is sufficient to focus on γ_i.

Given the cash flow's consumption beta, we inquire how much of the cross-sectional differences in expected returns are explained by this beta. That is, we consider the cross-sectional regression,

$$E[R_{i,t}] = \lambda_0 + \beta_{i,g}\lambda_c. \tag{13}$$

Equation (13) will be used extensively to evaluate the empirical plausibility of the cash flow beta model.

II. Data

A. 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 earlier work (e.g., Hansen and Singleton (1983)), aggregate consumption is measured as the 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 1.08% per quarter with a standard deviation of 0.65%. The mean of the quarterly real consumption growth rate series over the period spanning the first quarter of 1967 through the fourth quarter of 2001 is 0.52% per quarter with standard deviation of 0.44% per quarter.

The alternative set of models that we investigate are referred to as unconditional factor models. The particular models that we consider are C-CAPM, 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 1 month to maturity) on the value-weighted market portfolio. 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. 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 (γ_i or $\beta_{i,g}$) and cross-sectional risk prices are jointly estimated in one step. The GMM procedure that we follow is that proposed in Cochrane (2001) and consistent with Shanken (1992). This procedure corrects for the bias in standard errors generated by a two-pass regression. However, due to the size of the GMM system, we do not simultaneously estimate all the parameters of the VAR dynamics and the cross-sectional prices of risk when estimating the risk measure $\beta_{i,g}$. We pre-estimate the cash flow innovation, $\eta_{g_i,t}$, via the VAR, and then, simultaneously via the GMM procedure, estimate the cash flow beta, $\beta_{i,g}$ (see equation (12)), and the prices of risk. However, when we focus on the projection coefficient, γ_i, we estimate it simultaneously with the cross-sectional price of risk parameters in a full single-stage GMM system. This involves no pre-estimation. In addition, to evaluate our empirical work, we also provide finite-sample Monte Carlo evidence for the various risk parameters and R^2's of interest.

B. 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 toward understanding the risk compensation of a wider array of assets.

We utilize the dividends paid on these portfolios as our measure of cash flow. Our rationale for doing so is that the dividend paid on a portfolio is a cash flow quantity that is straightforward to measure. We discuss this measurement in greater detail below. Because we utilize dividends, which contain large firm-specific components and are highly seasonal, we focus on one-dimensional sorts on the characteristics discussed above, as this procedure typically results in over 150 firms in each decile portfolio.[3]

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[3] We also consider a 5×5 two-way sort on market capitalization and book-to-market resulting in 25 portfolios (see Fama and French (1993)). The general evidence, using this collection of portfolios is similar to what we document for our 30 assets; hence, we do not provide detailed results in the interest of brevity.

Table I
Summary Statistics: Portfolio Returns

The table presents descriptive statistics for the returns on the 30 characteristic-sorted decile portfolios. Value-weighted returns are presented for portfolios formed on momentum (M), market capitalization (S), and book-to-market ratio (B). The variable $M1$ 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 first quarter of 1967 through fourth quarter of 2001.

	Mean	Std. Dev		Mean	Std. Dev		Mean	Std. Dev
$S1$	0.0230	0.1370	$B1$	0.0154	0.1058	$M1$	−0.0104	0.1541
$S2$	0.0231	0.1265	$B2$	0.0199	0.0956	$M2$	0.0070	0.1192
$S3$	0.0233	0.1200	$B3$	0.0211	0.0921	$M3$	0.0122	0.1089
$S4$	0.0233	0.1174	$B4$	0.0218	0.0915	$M4$	0.0197	0.0943
$S5$	0.0242	0.1112	$B5$	0.0200	0.0798	$M5$	0.0135	0.0869
$S6$	0.0207	0.1050	$B6$	0.0234	0.0813	$M6$	0.0160	0.0876
$S7$	0.0224	0.1041	$B7$	0.0237	0.0839	$M7$	0.0200	0.0886
$S8$	0.0219	0.1001	$B8$	0.0259	0.0837	$M8$	0.0237	0.0825
$S9$	0.0207	0.0913	$B9$	0.0273	0.0892	$M9$	0.0283	0.0931
$S10$	0.0181	0.0827	$B10$	0.0327	0.1034	$M10$	0.0358	0.1139

B.1. 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 I, we present means and standard deviations of market value-weighted returns for size decile portfolios. The data evidences a small size premium over the sample period; the mean real return on the lowest decile firms is 230 basis points per quarter, contrasted with a return of 181 basis points per quarter for the highest decile. This dispersion in average returns is considerably smaller than for the remaining portfolio sorts.

B.2. 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 $t − 1$. 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 I. The data evidence a higher book-to-market than size spread; the highest book-to-market firms earn average real quarterly returns of 327 basis points, whereas the lowest book-to-market firms average 154 basis points per quarter.

B.3. 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 I. As shown, this sort provides the highest dispersion in mean returns among the firm characteristics. The highest decile firms earn an average real return of 358 basis points per quarter, whereas the lowest decile firms earn an average real return of -104 basis points per quarter. This spread of 462 basis points and the reported volatility of returns is comparable to the data in Fama and French (1996).

C. Portfolio Dividends

To explore the 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 and Shiller (1988). Let the total return per dollar invested be

$$R_{t+1} = h_{t+1} + y_{t+1}, \tag{14}$$

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).[4] We observe R_{t+1} (*RET* in CRSP terminology) and the price gain series h_{t+1} (*RETX*) 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

$$D_{t+1} = y_{t+1}V_t, \tag{15}$$

where

$$V_{t+1} = h_{t+1}V_t \tag{16}$$

with $V_0 = 1$. Hence, the dividend series that we use, D_t, corresponds to the total *cash* 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

$$R_{t+1} = \frac{V_{t+1} + D_{t+1}}{V_t} = h_{t+1} + y_{t+1}. \tag{17}$$

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

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[4] 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, $\frac{D_{t+1}}{V_t}$.

C.1. *Dividends and Repurchases*

Given the surge in repurchase activity over the latter part of our sample, we consider an alternative measure of payouts to equity shareholders that incorporates a candidate measure for repurchases. Denote the number of shares (after adjusting for splits, stock dividends, etc. using the CRSP share adjustment factor) as n_t. We construct the following *adjusted* capital gain series for a given firm:

$$h_{t+1}^{\star} = \left[\frac{P_{t+1}}{P_t} \right] \min \left[\left(\frac{n_{t+1}}{n_t} \right), 1 \right].$$ (18)

Note that this "capital gain" series will coincide with the CRSP capital gain series (*RETX*) associated with cash dividend payouts if $(\frac{n_{t+1}}{n_t})$ is bigger than or equal to 1. Only if there is a reduction in the number of shares, which is highly correlated with reported share buybacks, will the ratio $(\frac{n_{t+1}}{n_t})$ be less than 1. In this case, the CRSP capital gain series will be adjusted downward to account for the additional payout associated with any share repurchases. Hence, $h_{t+1}^{\star}$, the adjusted capital gain, is strictly less than or equal to the usual CRSP capital gain series. The construction of the repurchase adjusted dividends is exactly the same as in equation (15) save for using $h_{t+1}^{\star}$ as the capital gain series instead of h_{t+1}.

We construct the level of cash dividends, D_t, and dividends plus repurchases, $D_t^{\star}$, for the size, book-to-market, and momentum portfolios on a monthly basis. From this series, we construct the quarterly levels of dividends by summing the cash flows *within* the period under consideration. As these payout yields still have strong seasonalities at the quarterly frequency, we also employ a trailing four-quarter average of the quarterly cash flows 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 cash flow series. Summary statistics for the cash dividend growth rates of the portfolios under consideration are presented in Table II.

It is worth noting that our measure of repurchase activity reflects the same broad patterns reported using Compustat measures for repurchase activity reported in Jagannathan, Stevens, and Weisbach (2000).[5] In our context, however, the measure has the important advantage of employing CRSP data for measuring both returns and the repurchases augmented measure of dividends.

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[5] Repurchases are negligible prior to 1984; in 1983 our measure of repurchases totals $12 billion, compared to $68 billion in dividends paid. The amount repurchased surges in 1984 to $30 billion, hitting a peak in 1988, and dropping off through the early 1990s. Through the 1990s, the dollar amount rises substantially again; after 1997, the total amount repurchased exceeds that of cash dividends paid, peaking at $265 billion in 2000, compared to $179 billion in cash dividends paid. Hence, the overall patterns are quite consistent with the Compustat based evidence presented in Jagannathan et al. (2000), indicating that our repurchases measure is quite reasonable.

Summary Statistics: Portfolio Cash Flow Growth

The table presents descriptive statistics for the cash flow (dividend) growth rates on the 30 characteristic-sorted decile portfolios. Log differences in cash flows are presented for portfolios formed on momentum (M), market capitalization (S), and book-to-market ratio (B). The variable $M1$ 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 first quarter of 1967 through fourth quarter of 2001.

	Mean	Std. Dev		Mean	Std. Dev		Mean	Std. Dev
$S1$	0.0110	0.0549	$B1$	−0.0006	0.0395	$M1$	−0.0389	0.2281
$S2$	0.0099	0.0387	$B2$	0.0022	0.0512	$M2$	−0.0190	0.1296
$S3$	0.0075	0.0376	$B3$	0.0032	0.0723	$M3$	−0.0092	0.1120
$S4$	0.0065	0.0389	$B4$	0.0052	0.0694	$M4$	−0.0018	0.0804
$S5$	0.0069	0.0395	$B5$	0.0026	0.0471	$M5$	−0.0027	0.0896
$S6$	0.0034	0.0294	$B6$	0.0057	0.0319	$M6$	0.0019	0.0747
$S7$	0.0047	0.0366	$B7$	0.0048	0.0337	$M7$	0.0037	0.1037
$S8$	0.0037	0.0650	$B8$	0.0085	0.0404	$M8$	0.0122	0.0919
$S9$	0.0019	0.0417	$B9$	0.0078	0.0457	$M9$	0.0206	0.1220
$S10$	−0.0004	0.0182	$B10$	0.0109	0.0889	$M10$	0.0281	0.1784

III. Empirical Evidence

A. *Measuring the Consumption Exposure of Dividends*

In this section, we examine the relation between dividends and aggregate consumption growth. In particular, we focus on the implications of equations (7) and (12).

In Table III, we present two measures of the cash flow exposure to consumption shocks: γ_i, which represents the coefficient from a projection of portfolio-specific dividend growth on the moving average of consumption growth, and $\beta_{i,g}$, the regression coefficient from regressing cash flow news onto consumption news implied by the VAR. The projection coefficient from regressing the dividend growth innovation onto the consumption innovation, ϕ_i is also reported in Table III.

In estimating these risk exposures, the number of lags, K, of consumption growth in equation (7) is set at eight and the lag-length L, in equation (8) is set at four. Our results are not sensitive to the choice of L. In Section III.D.1, we show that our results are robust in including additional variables in the prediction of dividend growth rates. We also discuss at length the sensitivity of the results to the choice of K. Table III shows that our cash flow risk measures display striking patterns within the portfolio characteristic groupings. In particular, the large firm, low book-to-market, and loser portfolios display risk measures that are lower than those of the small firm, high book-to-market, and winner portfolios, respectively. That is, within these sorts, the two measures of cash flow beta reflect differences in mean returns.

<div align="center">

Table III

Portfolio Risk Measures

</div>

The table presents two alternative measures of the cash flow risk for 30 characteristic-sorted portfolios. Portfolios are formed on momentum (M), market capitalization (S), and book-to-market ratio (B). The variable $M1$ 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 first quarter of 1967 through fourth quarter of 2001. The column labeled "γ_i" presents the projection coefficient from the following regression

$$g_{i,t} = \gamma_i \left(\frac{1}{K} \sum_{k=1}^{K} g_{c,t-k} \right) + u_{i,t},$$

where $g_{i,t}$ represents *demeaned* log real dividend growth rates on portfolio i and $g_{c,t}$ the *demeaned* log real growth rate in aggregate consumption. Standard errors for this regression are reported in the columns labeled "SE," and associated R^2 are presented in the adjacent column. We also present risk measures and standard errors obtained from regressing the cash flow innovation on the consumption innovation, as in equation (10). These measures are presented in the columns labeled "$\beta_{i,g}$," and standard errors are presented in the adjacent columns. Finally, we present the slope coefficients from regressing the innovation in dividend growth rates, $\upsilon_{i,t}$, from equation (9), on the innovation in consumption growth, $\eta_{c,t}$. These coefficients are presented in the column labeled "ϕ_i" with standard errors in the adjacent column. Standard errors are corrected for heteroskedasticity and autocorrelation using the procedure in Newey and West (1987).

	γ_i	SE	R^2	ϕ_i	SE	$\beta_{i,g}$	SE		γ_i	SE	R^2	ϕ_i	SE	$\beta_{i,g}$	SE
$S1$	1.226	2.856	0.003	0.181	0.906	2.432	4.537	$B1$	2.987	2.896	0.039	0.582	0.672	5.903	5.133
$S2$	2.839	2.469	0.034	0.438	0.583	6.126	4.719	$B2$	−3.432	2.267	0.029	1.569	0.827	−3.637	4.126
$S3$	0.777	1.871	0.003	0.107	0.683	1.439	3.287	$B3$	0.021	2.391	0.000	0.390	1.458	0.441	4.180
$S4$	0.835	1.394	0.003	−0.317	0.695	0.966	2.135	$B4$	−0.282	2.811	0.000	−0.423	1.305	−0.922	4.790
$S5$	0.780	1.495	0.002	0.285	0.710	1.685	2.549	$B5$	0.462	1.810	0.001	−0.186	0.801	0.544	3.256
$S6$	1.952	1.083	0.028	0.349	0.475	3.832	2.154	$B6$	1.704	1.513	0.018	0.553	0.485	3.511	2.850
$S7$	1.392	1.600	0.009	0.192	0.692	2.513	2.825	$B7$	0.778	1.144	0.003	0.604	0.642	2.156	2.231
$S8$	1.146	1.671	0.002	1.221	1.068	2.801	2.947	$B8$	4.445	1.660	0.076	−0.178	0.657	6.967	3.143
$S9$	1.059	0.975	0.004	0.606	0.833	2.225	1.707	$B9$	4.735	3.077	0.071	1.035	0.630	10.308	4.916
$S10$	1.068	0.732	0.022	0.644	0.346	2.688	1.181	$B10$	8.440	4.076	0.057	2.165	1.558	16.652	7.654

	γ_i	SE	R^2	ϕ_i	SE	$\beta_{i,g}$	SE
$M1$	−8.907	7.549	0.010	1.733	3.791	−12.767	12.772
$M2$	−1.421	4.790	0.001	2.602	2.200	0.208	8.200
$M3$	−1.738	5.367	0.002	3.896	2.052	1.258	8.969
$M4$	−0.536	2.482	0.000	0.850	1.383	−0.054	4.134
$M5$	−0.740	3.819	0.000	3.053	1.578	1.968	5.563
$M6$	2.467	2.011	0.007	−0.355	1.348	3.735	3.770
$M7$	4.189	4.073	0.010	−1.703	1.810	5.012	6.968
$M8$	6.343	3.472	0.030	−2.804	1.536	7.437	6.406
$M9$	7.634	5.750	0.025	−0.808	1.694	11.580	10.043
$M10$	11.621	5.740	0.027	−4.370	2.925	15.186	12.363

This illustrates an important point; portfolios with high (low) risk measures ($\gamma_i, \beta_{i,g}$) are portfolios with high (low) average returns. That is, portfolios with higher 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 γ_i's, the winner and high book-to-market portfolio dividend growth rates demonstrate a close procyclical movements with the smoothed consumption growth rate. However, the loser portfolio dividend growth rate
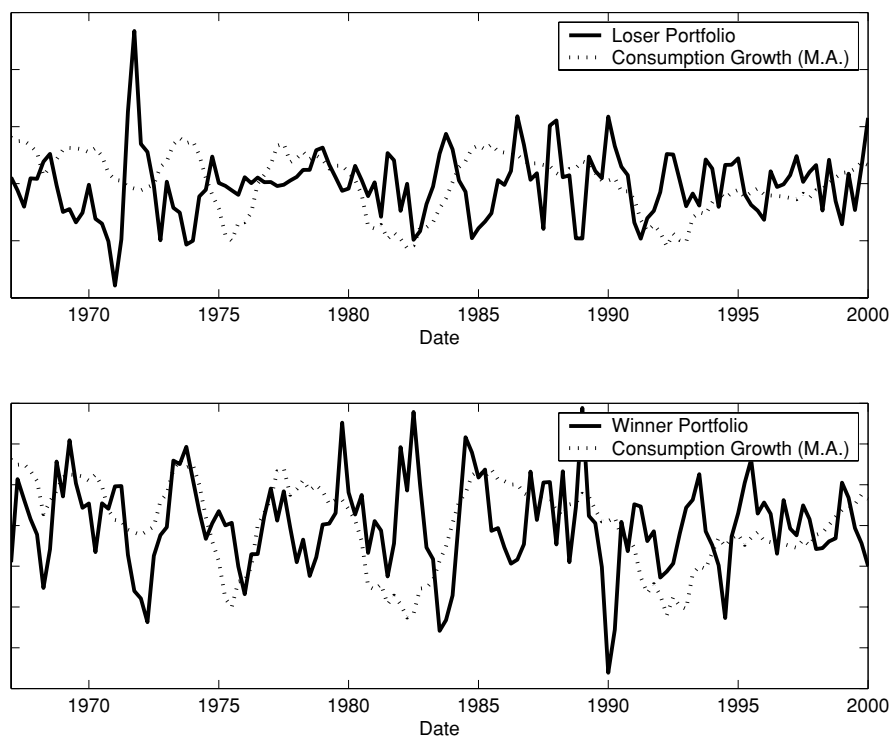
Figure 1. Momentum portfolios. The dividend growth series for the top and bottom momentum portfolios, as well as the trailing eight-quarter moving average of consumption growth.

demonstrates strong countercyclical 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 that of large firms, but the difference is less pronounced in accordance with the smaller size premium.

A striking feature of our results is that the constant exposure of the cash flow paid on momentum portfolios to aggregate consumption appears to be so closely connected to the average returns earned on these portfolios. Momentum has proven a particularly challenging dimension for asset-pricing models to explain; in particular, Fama and French (1996) show that momentum is the characteristic-sorted phenomenon that their three-factor model cannot explain. We discuss this issue in greater detail in Section III.B.2.

B. Equity Risk Premia in the Cross Section

In this section, we examine the relative performance of our cash flow beta model, the CCAPM, and standard unconditional factor models, in explaining
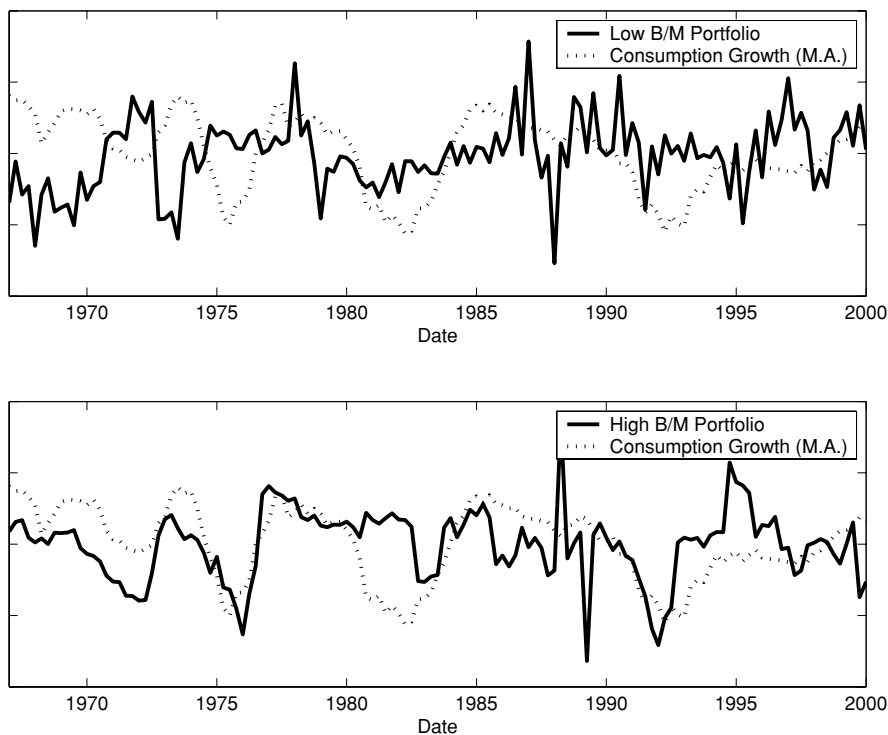
Figure 2. Book-to-market portfolios. The dividend growth series for the top and bottom book-to-market portfolios, as well as the trailing eight-quarter moving average of consumption growth.

the cross section of equity risk premia. In particular, we employ standard cross-sectional regression techniques (Jagannathan and Wang (1996), Lettau and Ludvigson (2001)) to analyze the contribution of the risk measure in our cash flow model and to explain the cross section of measured risk premia.

B.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. Table IV depicts results for measurement of cash flow risk via two methodologies: the projection of growth rates on lagged smoothed consumption growth (γ_i) and the fully specified VAR ($\beta_{i,g}$). The results indicate that for both measures of cash flow risk the price of risk is positive and strongly significant. When risk is measured by γ_i, the price of risk, λ_c, is estimated as 0.177 (SE = 0.072), and when measured by $\beta_{i,g}$ is estimated as 0.118 (SE = 0.027). In both cases, the model explains a considerable portion of the cross-sectional variation in risk premia; when risk is measured by γ_i,
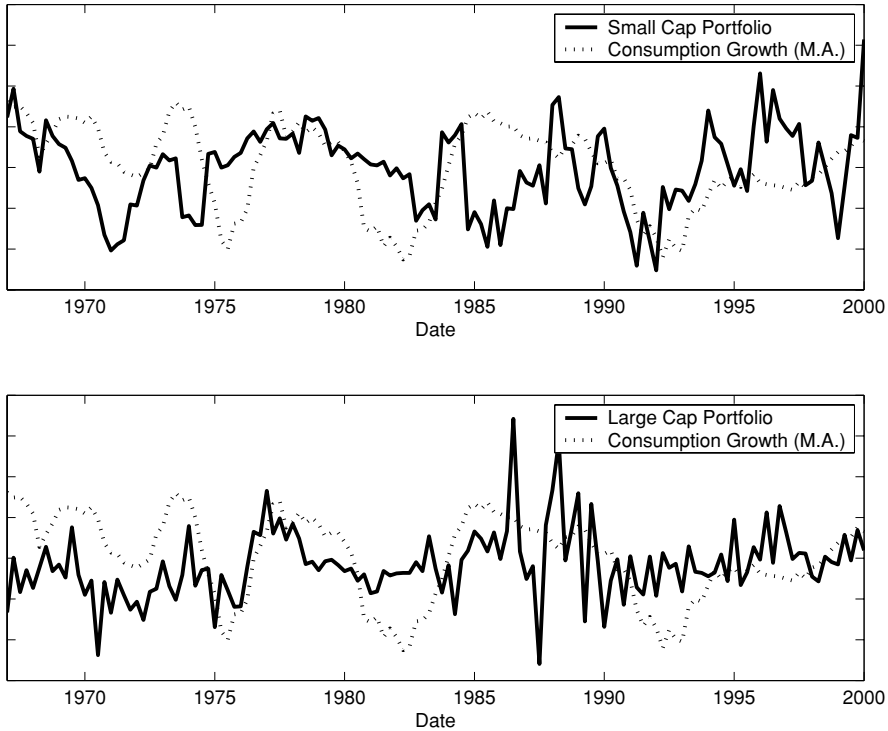
Figure 3. Size portfolios. The dividend growth series for the top and bottom capitalization port-folios, as well as the trailing eight-quarter moving average of consumption growth.

the adjusted R^2 is 66.3%, and when risk is measured by $\beta_{i,g}$, the adjusted R^2 is 62.0%.[6]

Graphical evidence of the performance of the model with the alternative risk measures is presented in Figure 4. As indicated in the figure, a particular success of the model is that it is capable of explaining much of the variation across momentum returns; γ_i is correlated with average momentum returns by 94%. This dimension is particularly challenging for the alternative models considered. However, the model's success is not limited to this dimension; in particular, the correlation between γ_i and average book-to-market returns is 71%. Across the size dimension, the risk measures and average returns are virtually uncorrelated, which is not surprising given the low dispersion in the average returns for this sort. However, the γ_i do reflect a size spread; the risk measure for the small firm portfolio exceeds that of the large firm portfolio. The overall message is clear: estimates of risk measures based solely upon the

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[6] As mentioned above, we also consider a 5×5 two-way sort on market capitalization and book-to-market resulting in 25 portfolios over the same time period. The cross-sectional R^2 for $\gamma_{i,g}$ is 48.3%, and the risk price is 0.249 (SE = 0.082), corroborating the evidence presented above for the single-dimension decile based sorts.

Table IV
Cross-sectional Evidence

The table 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. We utilize the log real cash flow growth rates to estimate two alternative risk measures, γ_i, and $\beta_{i,g}$. The measure γ_i is obtained from a projection of cash flow growth rates on a moving sum of lagged log real consumption growth; the measure $\beta_{i,g}$ is measured as the projection of cash flow innovations on consumption innovations obtained from a fully specified VAR structure. In Panel A, we report results of cross-sectional regressions of average real returns on these risk measures using log real dividend growth rates to measure cash flows. In Panel B, we repeat this exercise using a measure of log real growth in dividends plus repurchases. Risk prices are expressed in quarterly percentage terms. The data cover the period 1967, first quarter to 2001, fourth quarter, and are converted to real using the PCE deflator. The R^2 is adjusted for degrees of freedom.

	λ_0	λ_c	$\bar{R}^2$
	Panel A: Dividends		
	Independent Variable Is γ_i		
Coeff.	1.754	0.177	0.663
SE	(0.815)	(0.072)	
	Independent Variable Is $\beta_{i,g}$		
Coeff.	1.658	0.118	0.620
SE	(0.837)	(0.027)	
	Panel B: Dividends Plus Repurchases		
	Independent Variable Is γ_i		
Coeff.	1.741	0.166	0.607
SE	(0.851)	(0.057)	
	Independent Variable Is $\beta_{i,g}$		
Coeff.	1.697	0.105	0.456
SE	(0.859)	(0.030)	

relation between cash flows and consumption explain a considerable amount of the cross-sectional variation in measured risk premia.

The small differences in the explanatory power of $\beta_{i,g}$ and γ_i suggest that the covariance between the contemporaneous dividend growth rate innovation and the consumption innovation provides very little information regarding the cross section of average returns. Further, the larger standard error on the $\beta_{i,g}$ relative to γ_i for virtually every asset reflects the imprecision with which contemporaneous covariance is measured. This evidence suggests that it is dividend growth rate covariances with moderate to long lags of consumption growth that contain very valuable information regarding the cross section of risk premia.

The cash flow risk measures, γ_i and $\beta_{i,g}$, are estimated with considerable error. This is not surprising, as the the cash flow beta measures the discounted long run response of dividends to a consumption shock. The time-series R^2's based on the simple projection of dividend growth rates on the smoothed consumption are quite small, ranging from virtually 0 to approximately 7%. Our
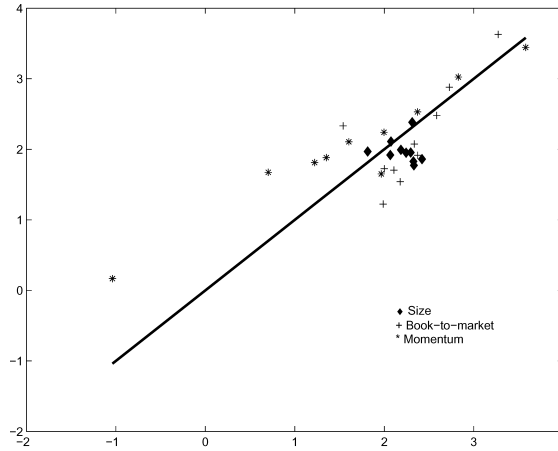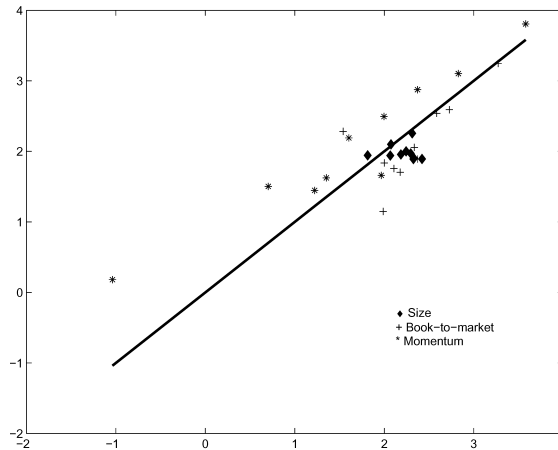
(a) Independent Variable Is $\beta_{i,g}$

(b) Independent Variable Is γ_i

Figure 4. Cross-sectional fit: cash flow beta model. The figure presents scatter plots for the cash flow model developed in the paper. The first figure presents results using the fully specified VAR measure of cash flow risk, $\beta_{i,g}$, whereas the second figure presents results using the projection of cash flows onto smoothed consumption growth, $\gamma_{i,g}$. The figures plot fitted expected returns against mean realized returns.

Monte Carlo evidence indicates that the moderate to large standard errors in estimating the cash flow risk measures are largely an indication of our finite samples. It is important to note, however, that the cross-sectional price of risk, λ_c, is positive and estimated very precisely.

In Section III.C, we report detailed Monte Carlo evidence that provides additional insights into our empirical findings. 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. The population values of λ_c and R^2 in the cross section are 0. The finite-sample empirical distributions show that our 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 betas are large, comparable to those observed in the data. However, the key parameters of interest, the cross-sectional R^2 and λ_c, are very precisely estimated. This shows that even in finite samples of 140 observations, there is little to no bias in the estimate of the cash flow betas in the time series, hence these betas continue to provide very valuable information regarding differences in mean returns in the cross section. In general, the economic value of the cash flow betas 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.

B.2. Cash Flow Betas and Momentum

Our evidence indicates that sorting on size and book-to-market sorts on exposure of cash flow growth rates to aggregate consumption. Our results indicate that sorting on past returns (momentum) also contains information about the average behavior of cash flows; that is, winners' cash flows seem to have larger consumption exposure relative to losers.

Why might the cash flow betas capture the mean return on momentum assets? Johnson (2002) presents a cash flow growth rate based argument. He shows the curvature with respect to growth rates of equity price (present values) is extreme. In particular, their log is convex in growth rates—hence, growth rate risk rises with growth rates. He argues that expected growth rates are persistent and high growth rates in the past translate into higher betas. Further, firms that have recently had a run up in prices are more likely to have had positive growth rate shocks relative to firms that have been poor performers. This, in conjunction with the fact that growth rate risk rises with growth rates, he shows, leads to a relation between past returns and expected returns along the lines found in the momentum sorts. The intuition presented in his model is consistent with our evidence; winner (loser) firms have higher (lower) average cash flow growth rates, and cash flow risk is priced.

B.3. Alternative Cash Flow Measure

As discussed above, dividends may not capture the entire cash flow stream paid to investors. One possibility for ameliorating this concern is to incorporate a measure of repurchases, as discussed in Section II.C.1. We repeat our estimation of risk prices in the cross section using γ_i and $\beta_{i,g}$, relying on the

cash flow measure of dividends plus repurchases rather than dividends. These results are presented in Panel B of Table IV.

As shown in the table, the results are quite similar to those presented for the measure of cash flows incorporating only dividends. The simple projection coefficient of dividends plus repurchases on smoothed consumption growth, γ_i, bears a risk premium of 0.166 (SE = 0.057) and explains approximately 60.7% of the cross-sectional variation in mean returns. This result compares favorably with those presented using dividends as the measure of cash flows. Similarly, the cash flow beta, $\beta_{i,g}$ explains 45.6% of the cross-sectional variation in expected returns, and bears a positive (0.105) and significant (SE = 0.030) price of risk. Thus, these results indicate that our measure of cash flow risk is reasonably insensitive to measuring cash flows as dividends plus repurchases.

B.4. Performance of Alternative 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 V documents the results of cross-sectional regressions in the context of standard unconditional models: the C-CAPM, the CAPM, and the 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 standard consumption-based C-CAPM, for which the associated risk premium restriction is as follows:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{i,c}\lambda_g, \qquad (19)$$

where $\beta_{i,c}$ describes an 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 consumption growth. The adjusted R^2 of 2.7% suggests little ability to explain the cross section of measured risk premia, and the price of risk, λ_g, of 0.022 is imprecisely measured (SE = 0.543). The inability of the unconditional C-CAPM to explain the portfolio returns is depicted graphically in Figure 5.

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

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw}, \qquad (20)$$

Table V
Alternative Models

The table 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. Four alternative specifications are examined. In the first specification, labeled "C-CAPM," risk is measured via a projection of real returns on log real consumption growth. In the second, labeled "CAPM," risk is measured via a projection of real returns on the real return on the CRSP value-weighted index. In the third set of results, labeled "Three-factor," risk measures are computed via a projection of returns on the return on the CRSP value-weighted index in excess of a T-Bill return (*MRP*), the return on a portfolio of small-capitalization stocks in excess of a portfolio of large-capitalization stocks (*SMB*), and the return on a portfolio of high book-to-market ratio stocks in excess of a portfolio of low book-to-market ratio stocks (*HML*). In the fourth set of results, labeled "Cash Flow Beta, SMB, and HML," we use the cash flow beta in addition to the size and book-to-market risk measures. Risk prices are expressed in quarterly percentage terms. The data cover the period 1967.1-2001.4, and are converted to real using the PCE deflator and R^2 are corrected for degrees of freedom.

	C-CAPM		
	λ_0	λ_c	$\bar{R}^2$
Coeff.	1.345	0.022	0.027
SE	(1.568)	(0.543)	
	CAPM		
	λ_0	λ_m	$\bar{R}^2$
Coeff.	3.709	−1.627	0.065
SE	(1.155)	(1.450)	

	Three-factor Model				
	λ_0	λ_{MRP}	λ_{SMB}	λ_{HML}	$\bar{R}^2$
Coeff.	9.730	−12.771	−3.845	3.841	0.362
SE	(2.171)	(3.992)	(2.039)	(1.433)	
	Cash Flow Beta, SMB, and HML				
	λ_0	λ_c	λ_{SMB}	λ_{HML}	$\bar{R}^2$
Coeff.	1.558	0.120	−0.174	0.014	0.594
SE	(0.700)	(0.027)	(0.778)	(0.587)	

where $\beta_{vw,i}$ describes an asset's exposure to market risk, and λ_{vw} describes the price of market risk. However, as in previous studies, the estimate of λ_{vw} is negative (−1.627) and the adjusted R^2 is only 6.5%. Again, the difficulty of the static CAPM in explaining the cross section of equity market returns is displayed graphically in Figure 5.

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:

$$E[R_{i,t+1}] = \lambda_0 + \beta_{vw,i}\lambda_{vw} + \beta_{SMB,i}\lambda_{SMB} + \beta_{HML,i}\lambda_{HML}. \qquad (21)$$
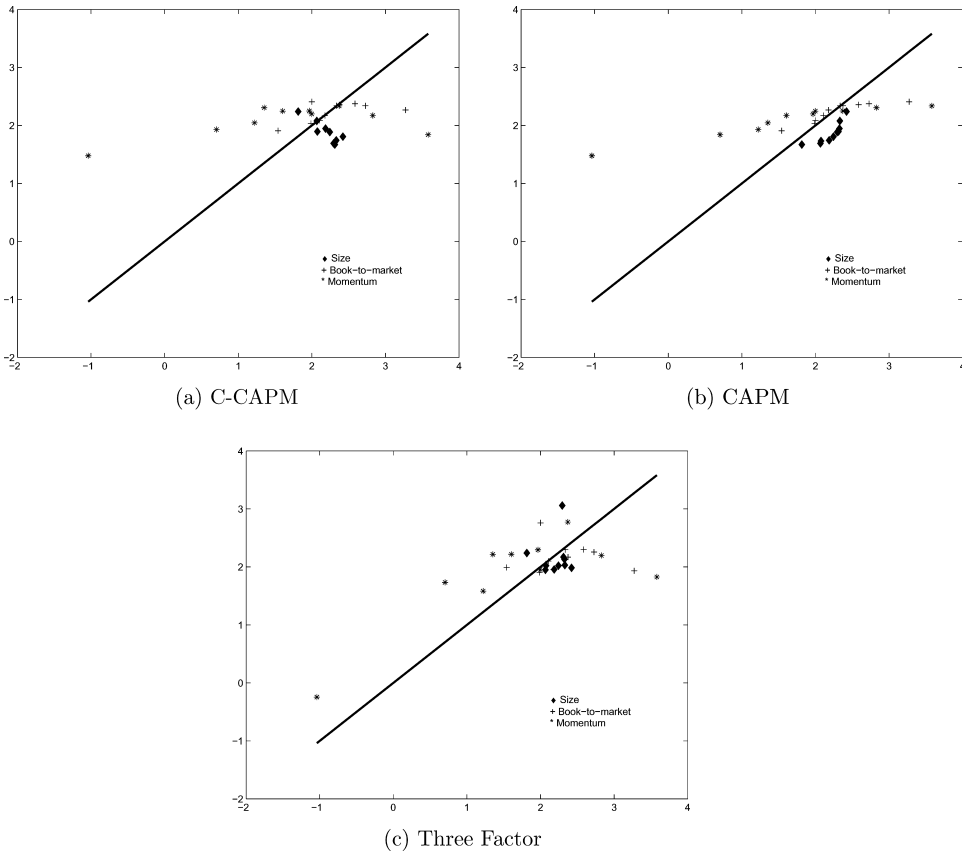
(a) C-CAPM

(b) CAPM

(c) Three Factor

Figure 5. Cross-sectional fit: alternative models. The figure presents scatter plots for the alternative models developed in the paper. The first figure presents results using the standard C-CAPM beta, the second figure presents results using the standard CAPM beta, $\beta_{i,vw}$, and the final figure presents results using three factors; the market risk premium, the return on a small capitalization portfolio in excess of the return on a large capitalization portfolio, and the return on a high-book-to-market portfolio in excess of the return on a low-book-to-market portfolio. The figures plot fitted expected returns against mean realized returns.

This model performs well relative to the single-factor alternatives considered thus far, but continues to have difficulty in explaining the cross section of risk premia. The model explains 36.2% of the cross-sectional variation in returns; the market portfolio and size factors have negative risk premia (-12.771 and -3.845, respectively) and the book-to-market factor has a positive risk premium (3.841). A graphical depiction of the model fit is provided in Figure 5. The negative risk premia on the market and size factors are inconsistent with the economic interpretations presented in Fama and French (1996).

These results indicate that the standard single-factor models (CAPM and C-CAPM) continue to have difficulty in describing the data. As argued in Fama and French (1996), the size and book-to-market factors may proxy for state variables that are not captured by the market portfolio or consumption growth.

We examine whether or not our cash flow beta is able to capture this information by performing the following regression:

$$E[R_i] = \lambda_0 + \lambda_c \beta_{i,g} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML}. \tag{22}$$

Results of this regression are presented in Table V. The results indicate that λ_c, the price of cash flow risk, remains positive and significant (0.120, SE = 0.027). This point estimate is similar to that in the univariate regression of the previous section. In contrast, the estimates of the price of *SMB* and *HML* risk are imprecisely measured and not significant. The explanatory power of the regression, as measured by the adjusted R^2 of 59.4%, suggests that these additional risk measures add little beyond the explanatory power of the cash flow beta.[7]

Bansal, Dittmar, and Lundblad (2001) also develop a risk measure based on stochastic cointegration between dividends and consumption. This risk measure is estimated via the projection of the deterministically detrended level of log dividends on the detrended level of log consumption. They document that this risk measure produces significant estimates for the price of risk and can account for a sizable portion (R^2's of approximately 50%) of the cross-sectional differences in risk premia across assets. The implications of this long-run relation between dividends and consumption for risk premia will be explored in subsequent research.

B.5. Asset Turnover

One issue that is raised in the interpretation of constant risk exposures pertains to the turnover in the portfolios. Liew and Vassalou (2000) document that the turnover in momentum portfolios is measurably higher than in size and book-to-market sorts. Consistent with their evidence, an average of 18% (14%) of the losers (winners) are also losers (winners) in the previous year in our data. As a benchmark, it is useful to also compare the turnover in momentum assets to the commonly used Fama–French (1992, 1993) 25 double-sorted portfolios. The average fraction of firms staying in a portfolio across the Fama–French 25 portfolios ranges from 26% to 75%. Over the sample and across portfolios, the turnover for any given year ranges from a low of 0 to a high of 100%. Hence, the turnover in the momentum assets and the Fama–French 25 portfolios is quite comparable.

To explore the issue of asset turnover and constant betas, consider the factor model described in equation (5). For simplicity, we will assume a single-factor structure for returns

$$r_{i,t} = \bar{r}_f + \beta_{i,g} \lambda + \beta_{i,g} \eta_{c,t} + \epsilon_{i,t}, \tag{23}$$

where the risk factor is $\eta_{c,t}$, the constant risk-free rate is $\bar{r}_f$, and the idiosyncratic shock is $\epsilon_{i,t}$. We simulate a time series of returns from this data-generating process, where (1) the betas are sampled with mean 1 and standard

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[7] Similar results are obtained using the alternative measure of cash flow risk, γ_i.

deviation of 20, (2) the factor innovation has standard deviation of 0.0025, and (3) the idiosyncratic shocks are normally distributed with mean zero and standard deviation σ_{ϵ_i}, where σ_{ϵ_i} is drawn from a uniform distribution between 0 and 0.06. The assumed characteristics of the betas and the factor innovation correspond to the distribution in our cash flow betas and the smoothed consumption innovation, respectively. We draw 140 observations of 1,000 firm returns, repeating the exercise 5,000 times.

Exactly as in the data, we sort the 1,000 firms into 10 momentum portfolios, resulting in only 18% of the firms staying in a given portfolio from one quarter to another. Despite the high turnover, the extreme winner portfolio has a mean return of 2.71% and the loser portfolio a mean return of -2.33%, and the average factor beta of the extreme winner (loser) portfolio is 14.39 (-12.39). What does the high turnover in the simulation exercise imply for the measurement of constant risk exposures? In our simulations, the beta of each portfolio does change through time, but the changes are small due to the cross-sectional averaging of the individual betas in a given portfolio. More importantly, standard (constant) portfolio betas constructed by regressing the portfolio returns on the factor have very high correlation with the average portfolio returns (correlation is over 95%). This indicates that although firms may switch into and out of these portfolios over time, the portfolio's standard constant beta may still capture much of the differences in expected returns. In the context of the momentum sorts, our simulation experiment indicates that high beta firms tend to be more often in the winner portfolio and low beta firms in the loser portfolio. Hence, on average, one is likely to see a mean spread across these portfolios with higher mean returns for the winner portfolio.[8] The main message of this simulation exercise is simply that despite the high turnover, constant betas are useful risk measures.

In the context of momentum sorts, it is worth noting that in the data a core of firms remain in their momentum decile for at least five years. About 11% of the firms designated as winners in year t remain winners in year $t + 1$ through $t + 5$, whereas 14% of the losers remain losers till $t + 5$. While much of the portfolio turnover is driven by short term return realizations, this evidence suggests that the measurement of portfolio risk may nevertheless be dominated by a core set of firms.

C. Monte Carlo Analysis

The evidence in the preceding sections suggests that the covariance of expected cash flow innovations with consumption innovations explains a considerable degree of the variation in risk premia across assets. As noted earlier, however, these exposures are measured quite imprecisely in the time series

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[8] Note that this argument is also presented in Conrad and Kaul (1998), while Jegadeesh and Titman (2001) argue that this is not the whole story. However, our evidence does not bear on this debate. Our simulation evidence is designed to simply point out constant betas are economically meaningful despite the turnover.

even though their associated price of risk, λ_c, is measured precisely and these risk measures explain an excess of the difference in expected returns across assets. 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. For both experiments, we explore both the simple risk measure, γ_i, and the full cash flow beta, $\beta_{i,g}$; however, the Monte Carlo implications across the two are nearly identical. Hence, for brevity, we only report results for the simpler measure, γ_i. In the first experiment, we simulate 10,000 samples of 140 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 betas are zero. Consumption growth is modeled as an i.i.d. process with an annualized standard deviation of 0.9% to match the data. We replicate the analysis above, projecting the *observed* dividend growth rates on the *simulated* consumption series to obtain the measures of cash flow risk $\hat{\gamma}_i$. We then regress *observed* average returns on the resulting risk measures. 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 parameters γ_i are zero by definition, 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 cash flow risk measures when the population values for all these quantities are zero.

The results of this experiment are presented in Table VI. The distribution of the estimates of γ_i are presented in Panel A. The risk measures are estimated with considerable error, but the distributions are approximately 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). For the simple measure of risk, γ_i, the point estimate of the risk price in the data is 0.177, which exceeds the 95th percentile of the empirical distribution. The cross-sectional adjusted R^2 exceeds the 90th percentile. This experiment indicates that the results that we observe in the data are in the right tail of the distribution, and 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 is extremely low.

Our second Monte Carlo experiment assumes the null hypothesis that our model is correct. Again, we simulate 10,000 samples of 140 quarterly observations of a consumption growth process. We assume that consumption growth follows an AR(1) process, where the parameters are chosen to match those observed in the data. We simulate the portfolio cash flows from the VAR system (10) using the point estimates of the parameter matrix A and means and standard deviations from the observed data; that is, the population time series R^2's

Table VI
Monte Carlo Evidence: Alternative Distribution

In this table, we analyze the distribution of the estimated parameters under the alternative hypothesis, that the cash flow beta model is incorrect. In particular, we simulate 10,000 samples of 140 quarterly time-series observations of aggregate consumption growth, assuming that the price of consumption risk and the cash flow betas are zero. Consumption growth is modeled as an i.i.d. process with the volatility of consumption growth set to match its counterpart in the data. We project *observed* dividend growth rates on *simulated* consumption growth rates to obtain the measures of cash flow risk $\hat{\gamma}_i$. We then regress *observed* average returns on the resulting risk measures using a single-step GMM procedure.

Panel A: Time-Series Parameters

	γ_i				
	5.0%	10.0%	50.0%	90.0%	95.0%
S1	−8.420	−6.589	0.003	6.638	8.405
S10	−2.560	−2.025	−0.001	2.054	2.585
B1	−6.155	−4.873	−0.012	4.852	6.243
B10	−12.268	−9.623	−0.062	9.398	12.334
M1	−24.198	−18.420	0.328	18.398	23.828
M10	−17.530	−13.689	−0.324	13.522	17.212

Panel B: Cross-Sectional Parameters

Ind. Var.	Price of Risk ($\lambda_c \times 100$)						$\bar{R}^2(\%)$									
	$\lambda_{c,0}$	2.5%	10.0%	50.0%	90.0%	97.5%	$\bar{R}^2_{cs}$	10.0%	20.0%	30.0%	40.0%	50.0%	60.0%	70.0%	80.0%	90.0%
γ_i	0.000	−0.141	−0.125	−0.003	0.105	0.136	0.000	−0.024	0.013	0.069	0.142	0.224	0.308	0.402	0.503	0.612

are identical to the (low) values presented in Table III. Returns are generated as

$$R_{i,t} = \lambda_0 + \gamma_i \lambda_c + \eta_{g_i,t}, \tag{24}$$

where $\eta_{g_i,t}$ is computed via expression (12).

The results of this experiment are presented in Table VII. As shown in the table, the point estimates for the time-series exposures, γ_i, under the null are centered at their population values, given by the estimates presented in Table III. However, the distributions around the medians are very large, commensurate with the evidence presented in the paper. In particular, the standard errors suggest that the null hypothesis that the risk measure is equal to zero cannot be rejected for any of these portfolios except for B10, even though the relationship is known to be true in the data. Thus, as in the data, we find that the risk measures are imprecisely estimated, which is a reflection of our small samples and large residual variance. In sharp contrast, we find that despite the time-series imprecision, it is still possible to recover positive and significant risk prices in the cross section. In fact, as shown in the table, the cross-sectional R^2 (which should be 1.00 under the null) and price of risk are downward biased due to sampling error in the risk measures. This actually suggests that, even under the null, the estimates are biased down making it even more challenging to recover the true priced relationship. Accordingly, our estimated price of risk and associated R^2 may be biased down and may represent conservative estimates of the true price of risk and R^2.

D. Discussion and Additional Checks

D.1. Predictability and the VAR Specification

How are the results affected by the number of lags in consumption growth used in the calculation of the cash flow betas? As shown in Table VIII, using fewer lags of consumption growth results in significantly poorer model performance. When covariances are measured relative to one-period lagged consumption growth rates and four-quarter smoothed consumption growth rates, the results deteriorate substantially. When $K = 1$, the risk premium is negative ($\lambda_c = -0.055$) and the explanatory power is negligible ($\bar{R}^2 = 0.072$). When $K = 4$, the results improve, but remain substantially poorer than those presented in the paper ($\lambda_c = 0.088$, $\bar{R}^2 = 0.121$). Results using γ_i are similar, as reported in the table. These results indicate that the cash flow and aggregate consumption links at horizons of about 2–3 years (about 8–12 quarters) are important for explaining the risk–return relation.[9]

As mentioned in Section I, the decomposition of price–dividend ratios into cash flow growth and discount rate components implies that this ratio

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[9] In the context of the market return, Daniel and Marshall (1997) also find that the relation between the market return and consumption at eight quarters was important for interpreting the market risk premium.

Table VII
Monte Carlo Evidence: Null Distribution

The table presents the distribution of parameter estimates and R^2 under the null hypothesis that the cash flow beta model is correct, with the point estimates of risk prices representing their population values. We simulate 10,000 samples of 140 quarterly observations of a consumption growth process; consumption growth is modeled as an AR(1) process where all parameters are set to match their counterparts in the data. We characterize cash flows using the VAR system (10) using the point estimates of the parameter matrix A and means and standard deviations from the observed data; that is, the population time-series R^2's are identical to the (low) values presented in Table III. Returns are generated as

$$R_{i,t} = \lambda_0 + \gamma_i \lambda_c + \eta_{g_i,t},$$

where $\eta_{g_i,t}$ is computed via expression (12).

Panel A: Time-Series Parameters

			γ_i		
	5.0%	10.0%	50.0%	90.0%	95.0%
S1	−2.403	−1.564	1.224	3.986	4.772
S10	−0.141	0.134	1.075	1.984	2.272
B1	0.330	0.967	2.982	4.965	5.552
B10	2.475	3.967	8.468	12.890	14.280
M1	−23.940	−20.500	−9.011	2.488	6.115
M10	−0.176	2.582	11.570	20.680	23.510

Panel B: Cross-Sectional Parameters

Ind. Var.		Price of Risk ($\lambda_c \times 100$)							$\bar{R}^2(\%)$							
	$\lambda_{c,0}$	2.5%	10.0%	50.0%	90.0%	97.5%	$\bar{\mathbf{R}}^2_{\mathrm{cs}}$	10.0%	20.0%	30.0%	40.0%	50.0%	60.0%	70.0%	80.0%	90.0%
γ_i	0.177	−0.017	0.023	0.100	0.185	0.237	1.00	0.03	0.09	0.16	0.22	0.29	0.35	0.41	0.49	0.58

should predict future cash flow growth. Consequently, in addition to including smoothed consumption growth in the VAR framework, we incorporate the log dividend yield as predictive variable. That is, we replace the first equation of expression (7) with the following equation:

$$g_{i,t} = \gamma_i \left(\frac{1}{K} \sum_{k=1}^{K} g_{c,t-k} \right) + \delta_i \, y_{i,t-1} + u_{i,t}, \tag{25}$$

where $y_{i,t-1}$ represents the demeaned log dividend yield of the asset and is assumed to be an AR(1) process. We present results for risk measures calculated using this alternative dynamic structure in Table VIII. As shown in the table, the incorporation of the portfolio dividend yield in the VAR results in some minor improvement in the explanatory power of the model. The simple coefficient on smoothed consumption growth, γ_i, explains in excess of 70% of the cross-sectional variation in average returns. The cash flow beta, $\beta_{i,g}$, explains 63% of this variation. The overall implications of the framework remain unchanged, as both measures bear positive prices of risk that are precisely estimated. These

Table VIII
VAR Dynamics

In this table, we consider alternative specifications for the VAR dynamics in the paper. In Panels A and B, we investigate alternative lag structures for the dependence of cash flows on consumption growth, $K = \{1, 4, 8, 12\}$. We present prices of risk, standard errors, and adjusted R^2 associated with cross-sectional regressions of average returns on risk measures. In Panel A, we examine the fully specified VAR risk measure, $\beta_{i,g}$, whereas in Panel B, we analyze the risk measure estimated relative to smoothed consumption growth, γ_i. In Panel C, we consider the possibility that asset-specific dividend yields help to predict cash flow growth. We incorporate the dividend yield into the VAR structure, with the standard eight-quarter moving average of consumption growth, and re-estimate the cross-sectional regressions for the resulting risk measure. The table presents the cross-sectional price of this alternative cash flow risk and the associated adjusted R^2.

	(a) $\beta_{i,g}$				(b) γ_i		
K	λ_c	SE	$\bar{R}^2$	K	λ_c	SE	$\bar{R}^2$
1	−0.055	(0.035)	0.072	1	−0.101	(0.130)	0.021
4	0.088	(0.038)	0.121	4	0.228	(0.072)	0.350
8	0.119	(0.027)	0.620	8	0.177	(0.072)	0.663
12	0.117	(0.024)	0.419	12	0.181	(0.068)	0.509

(c) Additional state variables			
	λ_0	λ_c	$\bar{R}^2$
Independent variable is γ_i			
Coeff.	1.827	0.189	0.754
SE	(0.818)	(0.041)	
Independent variable is $\beta_{i,g}$			
Coeff.	1.552	0.136	0.632
SE	(0.845)	(0.029)	

results indicate that the results are robust to the inclusion of additional state variables in the VAR framework.

Following the work of Bansal et al. (2001, 2002) other recent papers have also explored the information in cash flow betas for explaining the cross section of risk premia. Hansen, Heaton, and Li (2004) focus on the book-to-market portfolio sort, and consider various time-series specifications to measure the associated cash flow's consumption beta. Campbell and Vuolteenaho (2003) also focus on size and book-to-market portfolios, for which they measure portfolio return exposures to aggregate market cash flow news in the market portfolio. They do not rely on using observed cash flows to measure the cash flow news. Their cash flow news is the residual constructed from the innovations in the market return and the discounted expected market return. Given the focus on cash flow betas, our approach is to directly employ the cash flows in the data, model their dynamics, and extract the cash flow news to measure the cash flow beta.

The residual method need not coincide with our approach of directly relying on observed cash flows to measure cash flow news. For example, modeling expected returns using the set of predictive variables in Campbell (1996): the dividend yield, the "relative" risk-free rate, the aggregate equity market return, labor income growth, the term spread, and the consumption growth rate, we also extracted cash flow news as a residual. The consumption price of risks using this approach for our 30 portfolios is 0.278 (SE = 0.130), with a cross-sectional R^2 of 18%. The collection of momentum sorted assets is particularly challenging with cash flow betas based on this residual measure of cash flow news; the associated cross-sectional R^2 for the momentum portfolios is only 0.14. Bansal, Dittmar, and Lundblad (2004) further explore the implications of alternative ways of measuring cash flow news.

D.2. Characteristics

In this section, we examine whether certain portfolio characteristics contain additional explanatory power for the cross section of portfolio returns in addition to the risk measures investigated in this paper. We investigate this issue because several authors (Kan and Zhang (1999), Jagannathan and Wang (1998)) show that incorporating characteristics provides a useful diagnostic for the spuriousness of cross-sectional regressions. In particular, Jagannathan and Wang (1998) show that a useless factor cannot drive out a characteristic in a cross-sectional regression. Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), we incorporate the average log market value and average book-to-market ratio for each portfolio as characteristics in the regression.

Results of this analysis for the cash flow beta model and the C-CAPM are presented in Table IX. As shown in the table, after controlling for cash flow beta, as measured by $\beta_{i,g}$ and γ_i, size and book-to-market characteristics contain no residual information in explaining the cross section of average returns. In contrast, the price of cash flow risk, λ_c, remains positive and precisely estimated. Further, the portfolio characteristics, particularly book-to-market,

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Table IX

Characteristics

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The table presents results for cross-sectional regressions augmented by characteristics that have been shown to be related to average returns. In particular, we augment the cash flow beta model by the book-to-market variables and log market values. Results are presented using the fully specified VAR risk measure, $\beta_{i,g}$, as well as the risk measure estimated relative to smoothed consumption growth, γ_i. For comparison, results with the standard consumption CAPM (C-CAPM) beta are also presented.

	λ_0	λ_c	MV	BM	$\bar{R}^2$
		Independent variable is γ_i			
Coeff.	5.057	0.177	−0.179	−0.003	0.671
SE	(2.980)	(0.073)	(0.147)	(0.167)	
		Independent variable is $\beta_{i,g}$			
Coeff.	4.799	0.120	−0.167	−0.051	0.616
SE	(2.879)	(0.030)	(0.138)	(0.165)	
		C-CAPM			
Coeff.	5.709	−0.220	−0.162	0.444	0.076
SE	(4.367)	(0.226)	(0.198)	(0.223)	

retain residual explanatory power in C-CAPM regressions. This evidence suggests that the cash flow growth risk is capturing exposure to a priced factor, rather than a spurious factor.

D.3. C-CAPM and Time-Varying Discount Rates

The evidence presented in this paper suggests that cash flow betas capture a considerable portion of the cross-sectional differences in risk premia. This result is somewhat puzzling in light of the failure of the standard C-CAPM, as highlighted in this, and many previous, papers. Epstein and Zin (1991) and particularly Bansal and Yaron (2003) show that the consumption beta may not be sufficient to measure the risk of an asset—the betas of additional factors (e.g., shocks to consumption volatility) are priced as well. This channel may provide some insights as to why cash flow betas capture the cross-sectional differences in risk premia, while consumption betas do not.

Consider again the structure for return innovations presented in equation (5)

$$\eta_{i,t} = \beta_{i,g}\eta_{c,t} - \beta_{i,e}\eta_{e,t} + \epsilon_{i,t}.$$

The news components $\eta_{c,t}$ and $\eta_{e,t}$ correspond to consumption news and discount rate news respectively, and $\epsilon_{i,t}$ is the idiosyncratic noise in the asset's return. The cash flow beta is $\beta_{i,g}$, and let λ_c and λ_e be the market price of risks associated with the two systematic risk sources. If discount rate shocks and consumption shocks are uncorrelated, then the consumption and cash flow beta will coincide. In general, however, the cash flow beta and consumption beta will differ. The

standard consumption beta of the asset, measured via a return projection, is given by

$$\beta_{i,c} = \beta_{i,g} - \beta_{i,e}\tau\frac{\sigma_c}{\sigma_e}, \tag{26}$$

where τ is the correlation between $\eta_{e,t}$ and $\eta_{c,t}$, and σ_c and σ_e are the standard deviations of the consumption and discount rate news, respectively. The above expression shows that the consumption beta is a weighted combination of the two systematic risk betas, $\beta_{i,g}$ (cash flow beta) and $\beta_{i,e}$ (discount rate beta). Clearly, the consumption beta and cash flow beta can differ significantly. When multiple sources of risk are priced, solely using the consumption betas in the cross-sectional regression can produce a "tilt," and the estimated price of risk can be insignificant. If, however, one extracts the risk measure, $\beta_{i,g}$, from cash flows, then this should appropriately measure differences in risk premia attributable to cash flow risk, that is, λ_c. Consumption betas, in the presence of cash flow and discount rate risks, may fail to account for the differences in the risk premia across assets, which the cash flow betas may explain.[10]

In our discussion, we have focused on two risk factors, a cash flow risk factor and a single discount rate risk factor. It is straightforward to extend the example to multiple factors without changing the message. The point simply is that if asset returns have a multifactor structure, then consumption betas may fail to account for cross-sectional differences in risk premia. One must account for the individual betas corresponding to the underlying systematic risk factors in order to explain differences in risk premia across assets. Our empirical work indicates that the exposure of cash flow news to consumption identifies such a risk factor.

Another possibility is that the standard consumption beta fails to capture cross-sectional differences in risk premia due to error in the measurement of consumption (see Daniel and Marshall (1997)). In the presence of significant measurement error, estimated covariances between returns and consumption shocks may be contaminated. In contrast, the effect of measurement error on the predictive relationship between dividend growth and long lags of consumption growth may be less pronounced. Hence, despite the idiosyncratic noise in dividend growth, resulting cash flow betas may uncover a robust relationship lost in the standard constant beta C-CAPM regressions.

IV. Conclusion

The idea that differences in exposures to sources of systematic risk should justify differences in risk premia across assets is central to financial economics. In this paper we show that economic risks in cash flows can account for a

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[10] We investigate this issue a bit further by conducting a simple calibration. Using the return shocks in our data, $\eta_{i,t}$, and the estimated cash flow betas, $\beta_{i,g}$, we calibrate (1) exposures to the discount rate news, $\beta_{i,e}$, (2) τ, which is set at 65%, (3) σ_e, which is set at 0.01 per quarter. With this, the implied standard consumption betas exactly match those observed in the data. This produces a cross-sectional price of consumption beta risk close to zero with corresponding low cross-sectional R^2, while the price of cash flow beta risk is positive and produces an R^2 in excess of 60%.

significant portion of differences in risk premia across assets. The economic risks in cash flows is measured via the cash flow beta. These cash flow betas are derived using the joint VAR dynamics of observed cash flows and aggregate consumption growth rates. In particular, we compute the revision in expectations of the discounted sum of current and future cash flow growth rates (i.e., cash flow news). The exposure of this news to consumption innovations is the asset's cash flow beta.

These cash flow betas account for more than 60% of the cross-sectional differences in risk premia across 30 portfolios comprised of 10 size, 10 momentum, and 10 book-to-market portfolios. The risk premium associated with the consumption risk is positive and highly significant. Our cash flow betas' 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 betas and low risk premia. In sharp contrast, the winner portfolio and the high book-to-market portfolio have large positive cash flow betas and large positive risk premia. We document that our cash flow betas can account for much of the value (high book-to-market less low book-to-market), momentum (winner firm less loser firms), and size (small firm less large firm return) spreads. We also provide finite-sample empirical distributions for the various key parameters, such as the price of consumption risk. Our finite-sample distribution for the economic parameters of interest corroborates our empirical evidence.

We provide a multifactor interpretation as to why cash betas capture differences in risk premia, while standard consumption betas may fail to account for differences in returns across assets. In all, our empirical evidence suggests that economic risks in cash flows provide important information regarding the cross-sectional differences in risk premia across assets.

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