Interpreting Risk Premia Across Size, Value, and Industry Portfolios

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Abstract

In this paper, we model cash flow and consumption growth rates as a vector-autoregression (VAR), from which we measure the response of cash flow growth to consumption shocks. As the appropriate cash flow proxy is not unambiguous, nor likely to be measured without error, we consider three alternatives for portfolio cash flows: cash dividends, dividends plus repurchases and corporate earnings. We find that the *long-run* exposure of cash flows to aggregate consumption risk can justify a significant degree of the observed variation in risk premia across size, book-to-market, and industry sorted portfolios. Also, our economic model highlights the reasons for the failure of the market beta to justify the cross-section of risk premia. Most importantly, our results indicate that measured differences in the long-run exposures of cash flows to aggregate economic fluctuations as captured by aggregate consumption movements contain very valuable information regarding differences in risk premia. In all, our results indicate that the size, book-to-market and industry spreads are not puzzling from the perspective of economic models.

1 Introduction

The focus of this paper is to characterize the systematic sources of priced risks in the cross-section of returns from the perspective of general equilibrium models by appealing directly to the information embedded in the assets' cash flows. The empirical work of Hansen and Singleton (1982, 1983) underscores the importance of consumption risks in understanding risk premia. A consistent implication of these consumption based models is that the link between cash flows and aggregate consumption is a key input in determining an asset's exposure to and compensation for risk. Our approach emphasizes the long-run links between cash flows and consumption, and shows that this relation is empirically important for interpreting risk premia.

We concentrate on characterizing the sources of risk inherent in size, book-to-market, and industry sorted portfolios. These portfolios have been at the center of the asset pricing literature over the past two decades. These sorts produce economically meaningful risk premia; from 1949 through 2001, size sorted decile portfolios generate premia of 0.87% per quarter, book-to-market sorted portfolios generate premia of 1.51% per quarter, and industry groupings produce a spread of 0.83% per quarter. As the empirical literature has shown, the return premia of these dimensions pose a considerable challenge to economic models.

We explore the sources of these differences in average returns by examining the implications of a general economic model. In this model, returns are assumed to be generated by realized shocks to current and expected future cash flow growth. Further, asset cash flows are explicitly linked to the dynamics of aggregate consumption. In this setting, we show that differences in the long-run response of cash flows to a unit consumption shock (i.e., the cash flow beta) should explain cross-sectional variation in risk premia. When we additionally allow risk premia to fluctuate, we highlight some of the reasons why the usual market beta of an asset may fail to capture differences in risk premia across assets.

A key dimension of this paper is the measurement of long-run cash flow exposures to economic fluctuations. We model the consumption and cash flow growth rate dynamics as a vector autoregression (VAR). The cash flow beta for a given asset can be obtained from this VAR as the response of cash flow growth to a unit shock in consumption. Using only cash dividends, the first paper to focus on the empirical measurement of cash flow betas, Bansal, Dittmar, and Lundblad (2001), argues that covariation between dividend growth rates and consumption at long lags provides sharp information regarding risk premia on assets. In contrast to their paper, we provide the joint transition dynamics of cash flows and consumption in order to measure the cash flow betas. Since the appropriate cash flow associated with an equity claim is not unambiguous, we also estimate these relationships across three alternative candidate measures for cash flows: cash dividends, dividends plus repurchases, and corporate earnings. Further, it is also likely that observed cash flows are affected by high-frequency noise and corporate payout management. Hence, we determine whether long-run economic risk estimates are robust across several reasonable empirical candidates for equity payouts and the degree to which they are affected by high-frequency noise in their measurement. Additionally, we examine the links between cash flow betas and market betas, and analyze the reasons for the failure of standard market betas to capture risk premia across assets. Finally, we incorporate industry portfolios in our analysis, which pose their own unique empirical challenges as documented in Fama and French (1997).

As predicted by the theory, we find that the prices of risk associated with cash flow exposures to long-run economic risks are highly significant and positive across all three cash flow measures. To confirm our statistical inference, we conduct Monte Carlo experiments to examine the finite sample distribution of the price of risk and the cross-sectional R^2. This finite sample distribution accounts for estimation error in the VAR dynamics of consumption and dividend growth. For instance, the point estimate for the price of cash flow (for cash dividends) beta risk is 0.079, and highly significant, with an adjusted cross-sectional R^2 of 53%. Most importantly, we demonstrate that the component of the cash flow beta associated with the *long-run* exposure of cash flows to aggregate consumption fluctuations is the key parameter in explaining cross-sectional variation in observed premia. While the effects are somewhat less pronounced for the other two cash flow measures, this observation is robust, suggesting that both cash flow risk is a key component determining asset prices and can be detected by focusing on the long-run relationships between cash flows and the economy.

We present a model based on Epstein and Zin (1989) preferences, similar to that developed in Bansal and Yaron (2002). This model highlights the conditions under which the long-run cash flow exposure to aggregate risk will explain the cross-section of risk premia. Further, it also provides insights into the failure of the market betas to capture cross-sectional risk premia. In this model, asset returns are driven both by cash flow news and changing risk premia; the risk premium fluctuates due to changes in aggregate economic uncertainty (i.e., consumption volatility). The result is that the cross-section of risk premia is determined both by an asset's cash flow beta and its beta with respect to news about aggregate risk premia. The standard market beta is a weighted combination of these different betas, where each of these sources of risk bears a different price. Consequently, the market beta may fail to explain the cross-section of risk premia. The message implied by this evidence is that the cash flow beta is an important source of risk *in isolation*, and explains a considerable degree of the cross-sectional variation in observed risk premia.

In all, our empirical evidence indicates that the long-run exposure of cash flows to movements in the aggregate economy, as measured by consumption, contains very valuable information regarding differences in risk premia across assets. Cash flow streams that have larger exposure to aggregate consumption news also offer higher risk premia across several alternative cash flow measures. The work of Lettau and Ludvigson (2001) and Jagannathan and Wang (1996) highlight alternative channels for explaining differences in risk premia across assets. Our work augments the understanding of the determinants of risk premia by focusing on the links between cash flows and consumption.

The remainder of this paper is organized as follows. In section 2, we discuss the model for cash flow betas when discount rates are constant. Our strategy for estimating these betas is discussed in section 3. Section 4 discusses the empirical evidence. We analyze the economic implications of our framework in section 5. Section 6 provides concluding remarks.

2 Cash flow Betas

In this section, we provide the arguments that motivate our cash flow beta. For any asset i, consider the Campbell and Shiller (1988) linear approximation for the log return, $r_{i,t} = \ln(1 + R_{i,t}) = \ln(P_{i,t} + D_{i,t}) - \ln(P_{i,t-1})$:

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

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 $r_{i,t}$ the log return ($\kappa_{i,0}$ and $\kappa_{i,1}$ are parameters in the linearization). At this point, we abstractly interpret the cash flow, $D_{i,t}$, as the general payout to which the equity holder has claim. Empirically, there are important considerations associated with measuring equity cash flows, and this is one of the key issues we address in this paper (see Section 3).

Under this approximation (1), one can derive the following present value implication for the log price-cash flow ratio assuming the usual transversality condition holds:

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

Further, if we assume that expected returns are constant through time, the return innovation can be expressed as follows:

$$r_{i,t} - E_{t-1}[r_{i,t}] \equiv e_{r_i,t} = g_{i,t} - E_{t-1}[g_{i,t}] + E_t[\sum_{j=1}^{\infty} \kappa_{i,1}^{j} g_{i,t+j}] - E_{t-1}[\sum_{j=1}^{\infty} \kappa_{i,1}^{j} g_{i,t+j}] \tag{3}$$

Note that the case for which expected returns and expected cash flow growth rates may vary is considered in section 5.

2.1 Cash Flow Dynamics

To determine the long-run cash flow exposures to aggregate economic (consumption) shocks, we first must characterize the dynamic processes for consumption and cash flows. Log consumption growth, $g_{c,t}$, is assumed to follow an $AR(J)$ process

$$g_{c,t} = \mu_c + \sum_{j=1}^{J} \rho_{c,j} g_{c,t-j} + \eta_{c,t}, \tag{4}$$

and (log) cash flow growth rates follow

$$\begin{aligned} g_{i,t} &= \mu_i + \sum_{k=1}^{k=K} \gamma_{i,k} g_{t-k} + u_{i,t} \\ u_{i,t} &= \sum_{j=1}^{L} \rho_{j,i} u_{i,t-j} + b_i \eta_{c,t} + \zeta_{i,t} \end{aligned} \tag{5}$$

where $\zeta_{i,t}$ is uncorrelated with consumption innovations as stated above. Importantly, b_i measures the contemporaneous relationship between consumption and cash flow shocks, whereas, $\sum_{k=1}^{k=K} \gamma_{i,k}$ measures the long-run relationship between consumption and *future* cash flow growth rates. This distinction will be very important in our empirical analysis, as contemporaneous relationships may be contaminated by measurement error, whereas the long-run relationships (which are closely related to cointegration) are not (see Bansal, Dittmar, and Lundblad (2001)). Without loss of generality assume that $K \geq J$.

To characterize the evolution of the system, let $1 + (K + L) = q$. The $q \times 1$ vector z_t is

$$z_t' = [g_{i,t} \; u_{i,t} \cdots u_{i,t-(L-1)} \; g_{c,t} \cdots g_{c,t-(K-1)}] \tag{6}$$

The dynamics of consumption and cash flow growth can then be expressed as

$$z_t = \mu + A z_{t-1} + G u_t \tag{7}$$

where A and G are $q \times q$ matrices. Note that consumption feeds into the future dynamics of cash flows, but cash flows do not feed back into consumption. The $q \times 1$ vector u_t has its first elements as $\zeta_{i,t}$ and its last element as $\eta_{c,t}$; all other elements of u_t are zero.

To account for the linearization effect of κ_1, we define the matrix A_κ as $\kappa_1 A$. From equation (3), it follows that $e_{r_i,t}$ is the first element of the matrix

$$[I + \sum_{j=1}^{\infty} A_\kappa^j] G u_t = [I - A_\kappa]^{-1} G u_t \tag{8}$$

The cash flow beta, $\beta_{i,t}$, equals the first element of $[I - A_\kappa]^{-1} G \iota$, where ι has an element one corresponding to the consumption innovation and zero elsewhere. Note that the return innovation is

$$e_{r_i,t} = \beta_{i,d} \eta_{c,t} + \zeta_{i,t};$$

where $\beta_{i,d}\eta_{c,t}$ is the return response to aggregate consumption news and $\zeta_{i,t}$ represents the cash flow news specific to the asset. Note also that $\zeta_{i,t}$ and $\eta_{c,t}$ are uncorrelated. $\beta_{i,d}$ is determined by the reaction of the infinite sum of cash flow growth rates to consumption news; that is, the accumulated impulse response of cash flow growth rates to a unit consumption shock. We call $\beta_{i,d}$ the cash flow beta. In other words, this beta provides the response of the present value of *future* cash flow growth to a unit consumption shock.

To gain some intuition into what this risk measure captures, note that, for exposition, the cash flow beta with $K = L = J = 1$ is

$$\beta_{i,d} = \frac{\kappa_{i,1}\gamma_{i,1}}{1 - \kappa_{i,1}\rho_{c,1}} + \frac{b_i}{1 - \kappa_{i,1}\rho_{i,1}} \tag{9}$$

which reflects both the contemporaneous correlation between cash flow and consumption shocks, b_i, and the long-run exposure of current consumption growth on future dividends, γ_i. In general, the cash flow beta for asset i will be

$$\beta_{i,d} = \frac{\sum_k \kappa_{i,1}^k \gamma_{i,k}}{1 - \sum_j \kappa_{i,1}^j \rho_{c,j}} + \frac{b_i}{1 - \sum_l \kappa_{i,1}^l \rho_{i,l}} \tag{10}$$

When equality is imposed ($\gamma_{i,k} = \gamma_i$), then $\sum_k \kappa_{i,1}^k \gamma_{i,k} = \gamma_i \sum_k \kappa_{i,i}^k$. This expression measures the average covariance between cash flow growth and the lagged, K-period smoothed growth rate of consumption, and is what we employ in practice.

Next, we explore the ability of the estimated cash flow beta to explain the cross-sectional variation in observed average returns for market capitalization, book-to-market ratio, and industry sorted portfolios (30 portfolios in all). In section 5, we provide detailed economic motivation for why the cash flow beta should explain the cross-sectional differences in risk premia. This motivation leads to the specification

$$R_{i,t} = \lambda_0 + \lambda_c \beta_{i,d} + v_{i,t} \tag{11}$$

In equation (11), $R_{i,t}$ are the observed returns for asset i. The cross-sectional price of risk parameters λ_0 and λ_c, as shown in section 5, are determined by preference parameters. The above equation imposes the restriction that the differences in average returns across assets reflect differences only in $\beta_{i,d}$. This structure will form the baseline for our empirical analysis. However, as mentioned, we are concerned that high-frequency measurement noise and corporate payout management might affect the measured contemporaneous relationships. In contrast, we conjecture that the cash flow exposures to economic risk, γ_i, are robust to these considerations. Hence, in addition to cash flow beta, we also estimate the cross-sectional regression, (11), separating the contribution of the long-run risk exposures, γ_i, and the contemporaneous covariances, b_i. Note, if you assume that $b_i = 0$ in equation (10), the $\beta_{i,d}$ is a simple function of γ_i, and they contain the same cross-sectional information; under this assumption, cross-sectional R^2 will be identical (ignoring the approximation constants). Finally, we will subsequently explore the pricing implications of the cash flow beta in relation to standard CAPM market betas.

3 Data

3.1 Aggregate Cash Flows and Factors

Our empirical exercise is conducted on data sampled at the quarterly frequency from 1949-2001. We collect seasonally adjusted real per capita consumption of nondurables plus services data 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 quarterly real consumption growth rate series over the period spanning the second quarter of 1949 through the fourth quarter of 2001 is 0.0053 with standard deviation of 0.0050, and the mean of the inflation series is 0.0087 per quarter with a standard deviation of 0.0068. For subsequent analysis, we also measure the aggregate market portfolio return as the return on the CRSP value-weighted index of stocks.

3.2 Portfolio Menu

We consider portfolios formed on firms' market value, book-to-market ratio, and industry classification. Our rationale for examining portfolios sorted on these characteristics is that size and book-to-market based sorts are the basis for the factor model examined in Fama and French (1993). Additionally, industry sorted portfolios have posed a particularly challenging feature from the perspective of systematic risk measurement (see Fama and French (1997)). We focus on one-dimensional sorts on these characteristics as this procedure typically results in over 150 firms in each decile portfolio which facilitates a more accurate measurement of the consumption exposure of cash flows; it is important to limit the portfolio specific variation in cash flow growth rates, and a larger number of firms in a given portfolio helps achieve this.

Market Capitalization Portfolios

We form a set of value-weighted 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 decile portfolios.

The table displays a significant size premium over the post-war sample period; the mean real return on the lowest decile firms is 3.14% per quarter, contrasted with a return of 2.27% per quarter for the highest decile. The means and standard deviations of these portfolios are similar to those reported in previous work.

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 $t-1$.[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 1. The highest book-to-market firms earn average real returns of 3.76% per quarter, whereas the lowest book-to-market firms average 2.25% per quarter.

Industry Portfolios

Value-weighted industry portfolios are formed by sorting NYSE, AMEX, and NASDAQ firms by their CRSP SIC Code at the beginning of each month. Industry definitions follow those in Fama and French (1997). We specifically utilize definitions for ten industries: i1, consumer nondurables, i2, consumer durables, i3, oil, gas, and coal extraction, i4, chemicals and allied products, i5, manufacturing, i6, telephones and television, i7, utilities, i8, wholesale and retail, i9, financial, and i10, other.[2] Sample statistics for these data are also presented in Table 1. The mean real returns range from 2.04% for the Financial industry to 2.87% for Durable goods.

3.3 Measuring Cash Flows

3.3.1 Portfolio Cash Dividends

To measure the cash flow beta, we also need to measure the portfolio-specific cash flows described in the previous section. For our first candidate measure we extract the *cash*

[1]For a detailed discussion of the formation of the book-to-market variable, refer to Fama and French (1993).

[2]Industry definitions follow those provided by Kenneth French at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

dividend payments associated with each portfolio discussed in the previous section. Our construction of the dividend series is the same as that in Campbell (2000). Let the total return per dollar invested be

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

where $h_{1,t+1}$ is the price appreciation and $y_{1,t+1}$ the cash dividend yield (i.e., cash dividends at date $t+1$ per dollar invested at date t). More clearly stated, $h_{1,t+1}$ represents the ratio of the per dollar value of the portfolio at time $t+1$ to time t, $\frac{V_{1,t+1}}{V_{1,t}}$, and $y_{1,t+1}$ represents the per dollar cash dividends paid by the portfolio at time $t+1$ cash divided by per dollar value at time t, $\frac{D_{1,t+1}}{V_{1,t}}$. We directly observe both R_{t+1} and the price gain series $h_{1,t+1}$ for each portfolio; hence, we construct the cash dividend yield as $y_{1,t+1} = R_{t+1} - h_{1,t+1}$.[3] The level of the cash dividends we employ in the paper is extracted as follows

$$D_{1,t+1} = y_{1,t+1} V_{1,t}$$

where

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

with $V_{1,0} = 100$. Hence, the cash dividend series that we use, $D_{1,t}$, corresponds to the total cash dividends given out by a mutual fund at t that extracts the cash dividends and reinvest the capital gains. The ex-cash dividend value of the mutual fund is $V_{1,t}$ and the per dollar total return for the investors in the mutual fund is

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

which is precisely the reported CRSP total return for each portfolio.

3.3.2 Dividends and Repurchases

It is important to note that the payout strategy described above is only one of an infinite number that would be consistent with the reported CRSP total returns, R_{t+1}, on these portfolios. Additionally, given the surge in repurchase activity over the latter third of our sample, we consider an alternative measure for the payouts to equity shareholders that

[3]The price appreciation series, $h_{1,t}$ is equivalent to the ret_x series available in CRSP. At the portfolio level, this denotes the price appreciation for a mutual fund that pays out (without reinvestment) the *cash* dividend series.

incorporates a candidate measure for repurchases. Unlike previous research (see, for example, Jagannathan, Stevens, and Weisbach (2000) and Dittmar and Dittmar (2003)), we do not collect the reported repurchase activity from Compustat. Instead, our repurchases measure employs the information presented only in CRSP, but has the advantage of being completely consistent with the reported total return.

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.

$$h_{2,t+1} = [\frac{P_{t+1}}{P_t}] \cdot \min[(\frac{n_{t+1}}{n_t}), 1] \tag{12}$$

Note that this "capital gain" series will coincide with the CRSP capital gain series (ret_x) associated with cash dividend payouts if $(\frac{n_{t+1}}{n_t})$ is greater than or equal to one. That is, if the firm issues new shares or has no change in shares outstanding then the capital gain will be identical to $h_{1,t}$ above. Only if there is a reduction in the number of shares, which is highly correlated with reported share buy-backs, will the ratio $(\frac{n_{t+1}}{n_t})$ be less than one. In this case, the CRSP capital gain series will be adjusted downwards to account for the additional payout associated with any share repurchases. Hence, $h_{2,t+1}$, the adjusted capital gain, is strictly less than or equal to the usual CRSP capital gain series.

Given the adjusted capital gain series $h_{2,t}$, the total payout (cash dividend plus repurchases) yield, denoted $y_{2,t}$, is computed by $R_t - h_{2,t}$. As above, the payout level (cash dividends plus repurchases) is computed as

$$D_{2,t+1} = y_{2,t+1} V_{2,t}$$

where

$$V_{2,t+1} = h_{2,t+1} V_{2,t}$$

with $V_{2,0} = 100$. As above, the ex-payout (cash dividend plus repurchases) value is $V_{2,t}$ and the per dollar return for the investors in the mutual fund is

$$R_{t+1} = \frac{V_{2,t+1} + D_{2,t+1}}{V_{2,t}} \equiv h_{2,t+1} + y_{2,t+1}$$

which, as for the cash dividend case above, is exactly consistent with the reported CRSP total return R_{t+1}.

We construct the level of cash dividends, $D_{1,t}$, and dividends plus repurchases, $D_{2,t}$, for the size, book-to-market, and industry 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. Statistics for the annual cash dividends and dividend plus repurchases growth rates of the portfolios under consideration are presented in Table 1.

It is likely that this approximated measure of repurchase activity will differ somewhat from the reported Compustat measures. In Figure 1, we present actual US$ amounts for cash dividends and repurchases, separately, for the aggregate US market (NYSE, AMEX, and NASDAQ) from 1949 through 2001. As can be seen, prior to the early 1980's, the repurchases series is effectively zero, as share repurchase activity did not make up a significant component of payout strategy. However, repurchase activity picks up sharply in the mid-1980's through the present, but does display a strong cyclical pattern, dropping off significantly in the early 1990's and the last few years of the sample. Further, the time-series patterns are generally consistent with those presented in Jagannathan, Stevens, and Weisbach (2000). This evidence suggests that our repurchases measures, while not employing the actual reported values from Compustat, is a reasonable compromise, particularly considering that our measure is entirely consistent with the reported CRSP total returns.

In Table 1, we present average cash dividend and repurchase yields, separately, for each of the 30 firms under consideration.[4] Several interesting *cross-sectional* patterns emerge in the relative importance of cash dividends and repurchases across our asset menu. First, small capitalization firms exhibit lower relative cash dividend payouts relative to large firms. The average cash dividend yield for small firms is, on average, only 0.56% per quarter, whereas large firms have an average cash dividend yield of 0.93% per quarter. This is consistent with the idea that small firms retain more cash for investment. Interestingly, however, small

[4]Using our notation, the "cash dividend" yield presented in Table 1 is $y_{1,t}$ and, just for exposition, the "repurchase yield" is that component of payouts associated only with repurchases $y_{2,t} - y_{1,t}$. Of course, our second measure of cash flows, $D_{2,t}$, includes both cash dividends and repurchases.

firms do exhibit somewhat relatively larger repurchase yields at 0.25% per quarter versus 0.16% per quarter for large firms. On net, the total payout (cash dividends plus repurchases) is still significantly larger for large capitalization firms. Second, low book-to-market firms exhibit considerably lower cash dividend and repurchase yields relative to high book-to-market firms. Low book-to-market firms have a cash dividend yield of 0.58% per quarter and a repurchase yield of 0.13% per quarter. In contrast, the comparable measures for high book-to-market firms as 1.10% and 0.31% per quarter respectively, suggesting that so-called "value" firms, with potentially fewer growth opportunities, do indeed disburse a great deal more of their cash, in both dividend and repurchase form. We also observe some payout differences across industries. For example, the financials industry has a cash dividend yield of 1.50% per quarter with a repurchases yield of only 0.09% per quarter. In contrast, the chemicals industry appears to have a relatively large payout in both forms. The largest repurchases yield is associated with the non-durables goods industry at 0.21% per quarter.

The cross-sectional cash dividend and repurchases payout characteristics detailed above only reflect time-series averages across a half century of experience. Importantly, we know (see Figure 1) that the *relative* employment of these payout avenues has changed through time. For the extreme size (S1 and S10) and book to market (B1 and B10), Figure 2 shows time-series plots of the cash dividend and repurchases yields. As can be seen, in all cases, repurchases have become an increasingly important component of a firms payout strategy over time relative to cash dividends; however, this is considerably more pronounced for small and high book-to-market firms.

3.3.3 Portfolio Earnings

Finally, we consider an third measure of equity cash flow, by appealing directly to corporate earnings levels. In small samples, corporate earnings are admittedly not a precise measure of the exact payout to which equity holders have claim. Our conjecture is, however, that the long-run economic forces affecting overall cash payouts are the same as those affecting long-run corporate earnings, allowing us to detect low-frequency cash flow exposures. We view this issue as primarily an empirical question. If the long-run exposures to aggregate economic fluctuations are evident in cash dividends, dividends plus repurchases, and directly in corporate earnings, we have detected a risk source that is extremely important for understanding cross-sectional variation in expected returns. This would suggest that long-run economic risk spans several reasonable candidate measures for equity payouts, and most importantly, is unaffected by high-frequency noise in their measurement, which is known to plague both earnings and cash payouts. Further, this evidence would suggest that earnings and/or payout *management* is also a high frequency issue, and long-run economic risk affects the profitability of all firms regardless of short-run corporate strategy.

To explore this issue, we extract an earnings measure for each portfolio from Compustat. Quarterly Compustat earnings data are only available from 1962-2001; nevertheless, this sample still facilitates a important cross-check of the portfolio-specific exposures to long-run economic risk. In collecting the earnings data, we must first impose some initial screens. In order to be included in the calculation of portfolio earnings, firms must meet the following criteria:

1. Have valid Compustat income before extraordinary items (Quarterly Data Item 8) as of the end of the portfolio holding period, the month prior to the end of the holding period, or two months prior to the end of the holding period. That is, the firm must have had valid income before extraordinary items in the quarter of the holding period.

2. Have valid data for the characteristic in question (Book-to-Market Ratio, Capitalization, Capital Expenditures, or Industry) as of the ranking date for the characteristic.

3. Have valid market values as of the portfolio formation, valid total returns as of the end of the holding period, and valid capital gain returns as of the end of the holding period.

Earnings are then calculated as Income Before Extraordinary Items, Compustat (Quarterly data item 8) plus depreciation and amortization expense (Quarterly data item 5). The firm's earnings as of mm/dd/yy are treated as those for the fiscal quarter ending mm/dd/yy. For example, if a firm is in a given portfolio as of 6/30/99, and its fiscal year end is September, the earnings for the firm as of 6/30/99 are the 3rd quarter earnings for the fiscal year ending in 1999. Due to dating conventions, this is altered a bit for firms with fiscal year ends in January through May. If a firm is in a portfolio as of 6/30/99 and its fiscal year end is March, the firm's 6/30/99 earnings are those of the 1st quarter of the fiscal year ending in 2000. Portfolio earnings are the sum of earnings for the firms in the portfolio as of date mm/dd/yy.

Designate the aggregate sum of earnings on all firms in a particular portfolio at time $t+1$ as E^{agg}_{t+1}. We construct the earnings yield for this portfolio as follows:

$$y^e_{t+1} = \frac{E^{agg}_{t+1}}{\sum_{i=1}^{N} n_{i,t} \cdot P_{i,t}}$$

where, as above, $n_{i,t}$ is the number of shares outstanding and $P_{i,t}$ is the price per share for firm i (total number of firms equals N), so that $\sum_{i=1}^{N} n_{i,t} \cdot P_{i,t}$ is the aggregate total market capitalization for the collection of firms in this portfolio. We assume that the investor holds this portfolio as a mutual fund that reinvests the capital appreciation, $h_{1,t}$. Similar to our dividend construction, the level of earnings consistent with the mutual fund investment that we use in the paper is

$$E_{t+1} = y^e_{t+1} \cdot V_{1,t}$$

From this series, we construct quarterly levels of earnings by summing the level of earnings within a quarter. As above, we employ a trailing four quarter average of the quarterly earnings to construct the deseasonalized quarterly earnings series. These series are converted to real by the personal consumption deflator.

Since the union of the CRSP and Compustat sources are required to obtain portfolio earnings data, some firms are excluded. Hence, the size, book-to-market, and industry portfolios are slightly different from those constructed above. Also, given Compustat data limitations, we only measure quarterly corporate earnings over the 1965-2001 period. Hence, when we conduct cross-sectional regressions for the earnings-based risk measures, we will employ the associated average returns on the matched portfolios (and shorter time-period) presented here. In Table 2, we present summary statistics for the real total returns and earnings growth rates of the exact portfolios of firms that satisfy the above criteria. First, the general pattern in observed average returns across portfolios are nearly identical to those reported in Table 1 over the full post-war period for the broader collection of firms. The ability to explain these relative size and value spreads is still a challenge.

There is one important issue to address with regards to the earnings construction. While dividends (with or without repurchases as we measure them) will never be negative, measures of real corporate earnings may fall below zero for any of our portfolios. Indeed, for the small size (S1) portfolio, the real earnings are negative for the first two quarters of 1991 and over the last year of our sample (2001). Few of the other portfolios ever have negative values, except in the fourth quarter of 2001. In our empirical work, we measure the log growth rates consistent with the model specification, but given the (rare) appearance of negative values, earnings growth rates are constructed by taking the percentage change in the quarterly deseasonalized earnings series. For nearly all of our 30 portfolios, this is not an issue, and the cross-sectional regressions are not affected by the decision to employ log or simple growth rates. The earnings growth rates presented in Table 2 exhibit a considerably higher degree of volatility than the other two cash flow growth rate measures. In particular, the small firms and high book-to-market portfolios are very volatile. Note, however, much of this volatility is driven by the last two years of the sample when corporate earnings contracted sharply. If you exclude this period, earnings growth rate volatility is generally more in line (though somewhat still more pronounced) with the other cash flow growth measures. Most importantly, the inclusion of this period does not affect our cross-sectional estimates of long-run risk exposure, but does highlight the importance of high-frequency measurement issues, which are clearly pronounced during this period. Elevated earnings growth volatility makes the detection problem that much more challenging.

4 Estimation and Results

To explore the long-run relationship between consumption and our three candidate measures of cash flow growth (cash dividends, dividends plus repurchases, and earnings), we first estimate the dynamic processes described for consumption and cash flow growth rates. Note that in estimation we remove the unconditional mean from all the cash flow and consumption growth rate series and use these demeaned series in estimating the dynamics of consumption and cash flow growth rates. We use GMM, and consider the following set of moment conditions for estimation. First, the consumption dynamics can be estimated using the moment conditions:

$$E\left[\mathbf{g}_{0,t}\right] = E[\eta_{c,t} g_{c,t-j}] = 0 \tag{13}$$

for $j = 1 \cdots J$. This expression gives us J moment conditions associated with estimating the consumption dynamics. We estimate the cash flow growth dynamics with the following moment restrictions:

$$E\left[\mathbf{g}_{1i,t}\right] \;=\; \begin{pmatrix} E[u_{i,t}g_{c,t-k}] \\ E[u_{i,t-l}\zeta_{i,t}] \\ E[\eta_{c,t}\zeta_{i,t}] \end{pmatrix} = \mathbf{0} \tag{14}$$

for $k = 1 \cdots K$, and $l = 1 \cdots L$. The last moment condition estimates b_i. This expression yields $(K + L + 1)$ moment conditions for each cash flow growth under consideration, and J moment conditions associated with estimating the consumption growth dynamics. For N assets we consequently have $J + N(K + L + 1)$ moment conditions and the same number of parameters. We will set $J = 1$, $K = 8$ and $L = 8$. In addition, we also consider the cross-sectional restrictions

$$E\left[\mathbf{g}_{2,t}\right] = \begin{pmatrix} \sum_i E\left[R_{i,t} - (\lambda_0 + \lambda_c \beta_{i,d})\right] \\ \sum_i E\left[\left(R_{i,t} - (\lambda_0 + \lambda_c \beta_{i,d})\right)\beta_{i,d}\right] \end{pmatrix} = \mathbf{0} \tag{15}$$

The final two moment conditions ensure an exactly-identified system where the GMM based estimates for the relevant risk prices, λ_0 and λ_c, are equivalent to those obtained under ordinary least squares. Taken together, this yields $2 + J + N(K + L + 1)$ parameters, and the same number of orthogonality conditions. To explore the separate contributions of the long-run and the contemporaneous exposures, we also consider the cross-sectional regression of average returns on γ_i and b_i.

With 30 assets and 4 parameters to characterize the cash flow growth rates, the dimension of the optimal GMM weight matrix would be at least 120×120, which is impossible to estimate given the number of time-series observations. In practice, since the joint optimal GMM weighting matrix becomes too large, we utilize the following weighting matrix for the calculation of standard errors:

$$\mathbf{W}^{-1} = \begin{pmatrix} E\left[\mathbf{g}_{0,t}\mathbf{g}_{0,t}'\right] & 0 & \cdots & \cdots & 0 \\ \mathbf{0} & \left(E\left[\mathbf{g}_{1i,t}\mathbf{g}_{1i,t}'\right]\right) & \cdots & \cdots & \mathbf{0} \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ \mathbf{0} & \cdots & \cdots & \left(E\left[\mathbf{g}_{1N,t}\mathbf{g}_{1N,t}'\right]\right) & \mathbf{0} \\ \mathbf{0} & \cdots & \cdots & \mathbf{0} & E\left[\mathbf{g}_{2,t}\mathbf{g}_{2,t}'\right] \end{pmatrix} \tag{16}$$

That is, the weighting matrix is a block-diagonal matrix of the covariance of the moment conditions. The resulting weighting matrix is HAC-adjusted following Newey and West (1987). It is important to note that the standard errors on the time-series parameters for a given (univariate) dividend growth rate utilize the full GMM weight matrix—and hence are quite reasonable. The system associated with the estimating the risk prices is exactly identified; that is, the point estimates correspond to the OLS estimates. However, the standard errors for the risk prices, that is λ_0 and λ_c, do not take account of the error in estimating the time-series parameters that go into the construction of the cash flow betas. For this reason, we also report the Monte Carlo finite sample distribution for the t-statistic on the estimated risk prices and the cross-sectional R^2 that takes account of the estimation error of all the time series and cross-sectional parameters for all assets at the same time. The details of this Monte Carlo are provided in the next section.

4.1 Empirical Evidence

For the purposes of estimation, we assume that the log consumption growth rate, $g_{c,t}$, follows an AR(1) process; that is, we assume $J = 1$. The smoothed consumption growth, $\tilde{g}_{c,t}$, is measured over eight quarters ($K = 8$); consequently, we assume an AR(8) for the shocks to the cash flow growth rate, $u_{i,t}$ ($L = 8$).[5] Additionally, we assume that $\gamma_{i,k} = \gamma_i \quad \forall \quad k$. Taken together, the dynamic process for the *demeaned* quarterly consumption and cash flow growth rate data that we consider:

$$
\begin{aligned}
g_{c,t+1} &= \rho_c g_{c,t} + \eta_{t+1} \\
g_{i,t+1} &= \gamma_i \tilde{g}_{c,t} + u_{i,t+1} \\
u_{i,t+1} &= b_i \eta_{t+1} + \sum_{l=1}^{L} \rho_{l,i} u_{i,t-l+1} + \zeta_{i,t+1} \\
\beta_{i,d} &= \frac{K \kappa_{i,1} \gamma_i}{1 - \kappa_{i,1} \rho_c} + \frac{b_i}{1 - \sum_l \kappa_{i,1}^l \rho_{l,i}} \qquad (17)
\end{aligned}
$$

In this case, the cash flow beta, $\beta_{i,d}$, is determined both by the contemporaneous covariance between the cash flow and consumption shock, b_i, and the effect the smoothed consumption growth rate has upon future cash flows, embodied in the coefficient γ_i; in both cases, the

[5] Results are not sensitive to the order of the AR process for the cash flow growth rate shocks.

autoregressive nature of the processes magnify the effects accordingly.[6] Note, our results appear to be qualitatively robust to alternative choices for K and L.

For our first candidate measure of cash flows, cash dividends, the parameter estimates for this model are presented in Table 3. Estimates of γ_i for the characteristic-sorted portfolios are presented in Table 3 along with HAC-adjusted standard errors. As shown in the table, a clear pattern emerges in the projection of cash dividend growth rates on the smoothed average of lagged consumption growth rates. Sorting on market capitalization produces a pattern in γ_i. For example, the small firm portfolio exhibits a covariance with smoothed consumption growth of 1.76 (S.E. 2.12) compared to 0.09 (S.E. 0.70) for the large firm portfolio. The pattern is most pronounced *within* the decile sort. Also, the book-to-market sorted portfolios produce large spreads in γ_i; the high book-to-market firms' sensitivity to smoothed consumption growth is 8.48 (S.E. 2.73) compared to 1.27 (S.E. 2.38) for the low book-to-market firms. The pattern among industry-sorted portfolios is less identifiable. In untabulated results, we find that the pattern in the long-run exposure to consumption fluctuations is very similar across our other candidate cash flow measures: dividends plus repurchases and earnings. This evidence suggests that exposures to long-run economic risk are evident in all our candidate measures of cash flow, and for this reason, we present the cross-sectional implications of these patterns below. Despite strong cross-sectional significance across all our cash flow measures documented below, the estimates of γ_i are associated with large standard errors. Monte Carlo evidence presented below confirms that the cross-sectional evidence is nevertheless robust even when accounting for the time-series imprecision of the long-run exposure, γ_i.

We also present the contemporaneous covariance between the consumption and cash flow growth rate shocks, b_i, in Table 3. This parameter measures the immediate response of each asset's cash flow growth rate to an aggregate shock. For cash dividends, sorting on market capitalization and book-to-market produces a strong pattern in the contemporaneous relationship between consumption and cash dividend shocks. However, in untabulated results, this pattern is not pronounced for our other measures of cash flow, dividends plus repurchases or earnings. The contemporaneous covariances, b_i's, for these alternative measures are not consistent across candidate cash flow measures. This suggests that measurement noise

[6]Note, that $\kappa_{i,1}$ is estimated to be equivalent to $1/(1+exp(\overline{d-p}))$, where $(\overline{d-p})$ is the average log cash flow-price ratio. For cash dividends, $\kappa_{i,1}$ is, on average, 0.988 for quarterly data. Incorporating $\kappa_{i,1}$ in the calculation of the cash flow beta does not materially impact our results. For example, if we assume $\kappa_{i,1}$=1 for all assets, our results are materially unchanged.

and/or payout management is driving a wedge between the high-frequency relationships among cash dividends, repurchases, and earnings.

In Table 3, we also document the sum of the autoregressive coefficients for the portfolio-specific cash dividend growth rate shocks (the evidence for the other cash flow measures are comparable). Many of these coefficients are reasonably large and significant. Additionally, the first order autocorrelation coefficient in consumption growth is estimated to be 0.25 (S.E. 0.07). Our estimates of the cash flow beta (see equation (17)) will utilize this serial correlation.

Finally, we also present the implications of the previously estimated parameters for the cash flow beta, $\beta_{i,d}$, for each of the 30 portfolios implied by the cash dividends. This is a key parameter of interest, as it describes each portfolio's dividend response to an aggregate consumption shock. Further, according to the model presented above, this parameter is the sole measure of exposure to systematic risk which determines risk premia in the cross-section. Accordingly, we will explore the ability of the cash flow beta to explain cross-sectional variation in average returns across the 30 portfolios. As can be seen in equation (17), the cash flow beta is essentially the sum of the projection coefficient describing the long-run exposure of cash dividend growth to smoothed consumption, γ_i, and the contemporaneous covariance between shocks to cash dividend and aggregate consumption growth, b_i, adjusted for serial correlation in each series. Empirically, the estimated cash flow betas differ dramatically across the portfolios, generally in line with their observed average returns. For example, we document a large cash flow beta spread in market capitalization portfolios; the $\beta_{i,d}$ for the small firm portfolio is 2.65 (S.E. 1.84), whereas the same for the large firm portfolio is only 0.76 (S.E. 0.40). The same pattern emerges for the book-to-market sorted portfolios; the estimated $\beta_{i,d}$'s for the low and high book-to-market portfolio are 1.73 (S.E. 1.18) and 5.02 (S.E. 1.87), respectively, in line with the large observed dispersion in average returns across high and low book-to-market portfolios. Finally, a less pronounced pattern emerges with the industry sorted portfolios, with the durable goods industry displaying the largest, by far, estimated cash flow beta at 2.90 (S.E. 1.10). The lowest cash flow beta among the industry-sorted portfolio is associated with the chemicals industry. HAC-adjusted standard errors, computed using the delta method, demonstrate that the cash flow betas are generally estimated with precision in the time-series. In untabulated results, we observe less pronounced patterns in the cash flow betas for the dividend plus repurchases and earnings measures. However, they continue to be consistent with the observed size and value spreads.

In the next section, we will explore, for each of our candidate cash flow measures, the ability of the cash flow betas (and their associated components b_i and γ_i) to explain average returns.

4.2 Cash Dividend Betas and the Cross-section of Returns

In this section, we examine the ability of the cash flow beta, $\beta_{i,d}$, to explain the cross-sectional variation of observed equity risk premia. Effectively, we perform standard cross-sectional regressions using the 30 decile portfolios (10 size, 10 book-to-market, and 10 industry). The estimated cross-sectional risk premia restriction is stated in equation (15), with λ_0 and λ_c as the cross-sectional parameters of interest, given the estimated cash flow beta. For cash dividends, $D_{1,t}$, Table 4 (Panel A) documents the ability of the estimated cash flow betas to explain the cross-section of average returns. For this measure of payouts, our results demonstrate that the estimated price of consumption risk is both positive and significant; the OLS estimate of λ_c is 0.079, with a HAC-adjusted t-statistic of 2.41. The GMM based standard errors account for the time-series variation in measured returns. Further, the adjusted R^2 is 53%. Within portfolios sorts, this relationship holds as well; for example, the correlations between average returns and the cash flow betas are 0.46, 0.75, and 0.18 for the size, book-to-market and industry portfolio, respectively. Consistent with the large cross-sectional R^2, the estimated cash flow beta can explain a considerable portion of the cross-sectional variation in measured risk premia associated with this set of portfolios.

To explore the small-sample features of our estimator, we conduct a simulation-based Monte Carlo analysis. The small sample distribution may be particularly important since the cash flow beta is not always precisely measured in the time-series. For most of the portfolios, $\beta_{i,d}$ is significantly different from zero, but the projection of cash dividend growth on lagged consumption growth, γ_i, is generally not. Despite this issue, the cross-sectional price of consumption risk, λ_c, does appear to be estimated precisely with more than 50% of the cross-sectional dispersion in risk premia explained. Collectively, this requires more careful consideration, and in consequence, we consider an additional simulation based experiment to ensure that our results reflect the economic content of our model rather than random chance.

We conduct the following Monte Carlo experiment, in which we simulate 10,000 samples of quarterly measured aggregate consumption growth of the same size as is available in our sample (1949-2001). This experiment simulates under the alternative hypothesis that our model is incorrect. That is, we effectively assume that the price of consumption risk and the cash flow beta, $\beta_{i,d}$, are zero. The demeaned consumption is simulated from an AR(1) process

$$\hat{g}_{c,t+1} = \hat{\rho}_c \hat{g}_{c,t} + \hat{\eta}_{c,t+1} \tag{18}$$

where $\hat{\rho}_c$ is the autoregressive parameter for consumption estimated in the data, and $\hat{\eta}_{c,t+1}$ is simulated from a normal distribution with standard deviation equal to σ_η, which corresponds to the standard deviation of the consumption growth residual in the data. The simulated consumption growth rates and demeaned *observed* cash dividend growth rates are used to estimate the time-series parameters in equation (17). That is, we re-estimate the cash flow beta for each iteration as follows:

$$\begin{aligned}
\hat{g}_{c,t+1} &= \rho_c \hat{g}_{c,t} + \hat{\eta}_{t+1} \\
g_{i,t+1} &= \gamma_i \tilde{\hat{g}}_{c,t} + u_{i,t+1} \\
u_{i,t+1} &= b_i \hat{\eta}_{t+1} + \sum_{l=1}^{8} \rho_{l,i} u_{i,t-l+1} + \zeta_{i,t+1} \\
\beta_{i,d} &= \frac{8\kappa_{i,1}\gamma_i}{1-\kappa_{i,1}\rho_c} + \frac{b_i}{1-\sum_{l=1}^{8}\kappa_{i,1}^{l}\rho_{l,i}}
\end{aligned} \tag{19}$$

where each portfolio's demeaned cash dividend growth rate, $g_{i,t}$, is the actual observed quantity for each portfolio, and $\tilde{\hat{g}}_{c,t}$ is the 8-quarter smoothed simulated consumption growth rate. For each iteration, we then run the standard cross-sectional regression:

$$R_{i,t} = \lambda_0 + \lambda_c \beta_{i,d} + v_{i,t} \tag{20}$$

where $R_{i,t}$ is the *observed* real return for each portfolio. As the simulated consumption growth is independent of all the cash dividend growth rates, by construction, the population values of the cash flow betas, $\beta_{i,d}$, are zero, and therefore the population value of λ_c is also zero. This Monte Carlo experiment provides finite sample empirical distributions for the t-statistic on the estimated λ_c and the adjusted R^2 for the cross-sectional projection. For each iteration, we store the HAC-adjusted t-statistic and the $\bar{R}^2$.

The results of this experiment are presented in Table 4. The distribution for the HAC-adjusted t-statistic on the estimated price of risk, λ_c, and the cross-sectional adjusted R^2 are presented in Panel A. The t-statistic distribution is essentially centered at zero (the population value) for both frequencies. This evidence suggests that our point estimates for λ_c are statistically significant, as our estimated t-statistic of 2.41 is in the far right hand tail of the empirical distribution. These t-statistics are at the 95% quantile, which is consistent with a rejection of the null hypothesis that no *positive* cross-sectional relationship exists at the 5% confidence level. As additional evidence in favor of the relationship between the measured average returns and the cash flow beta, an $\bar{R}^2$ of 53% is in the far right tail of the adjusted R^2 empirical distribution for these data, exceeding the 97.5% critical value. Collectively, this experiment suggests that our empirical results reflect the true economic content of the estimated cash flow beta rather than random chance. In an economy in which asset returns and cash dividend growth are independent of consumption growth, the probability of observing these estimated magnitudes of λ_c and the cross-sectional $\bar{R}^2$ is extremely low.

We also consider the relative contributions of the components that comprise the cash flow beta. In particular, we explore the cross-sectional regression in equation (20), replacing $\beta_{i,d}$ with the estimate of the cash dividend exposure to long-run consumption fluctuations, γ_i. The results of this regression are presented in Panel A of Table 4. As can be seen, the estimated "price of risk" associated with the long-run exposure, γ_i, is both positive and significant, with a cross-sectional $\bar{R}^2$ of 53%, identical to the cash flow beta regression. Note, if we assume that $b_i = 0$ for all assets, the cross-sectional $\bar{R}^2$'s would be identical for either γ_i or $\beta_{i,d}$; that is, they would contain exactly the same cross-sectional information. To explore this issue further, we consider the joint regression of average returns on both γ_i and b_i. For cash dividends, the risk price associated with the long-run exposure continues to be both positive and significant, whereas the contemporaneous covariance is statistically insignificant. Taken together, this evidence suggests that γ_i provides the major contribution to the explanatory power of the cash flow beta. In other words, b_i=0 might be a reasonable assumption, particularly if we are concerned that b_i is contaminated by high-frequency noise. We conduct an additional Monte Carlo experiment to explore the small-sample properties of these two alternative cross-sectional regressions and, in particular, the estimate price of risk on the long-run exposure, γ_i, since it is known to be estimated with imprecision in the time-series. As can be seen, the cross-sectional $\bar{R}^2$ of these regressions exceed the 97.5% critical value. Additionally, the t-statistics on the associated risk price exceed the 95% quantile. The long-run exposure of cash dividends to consumption growth is the key factor explaining cross-sectional variation in average returns.

4.3 Alternative Cash Flow Measures and the Cross-section

As we have mentioned, the cash dividends associated with our asset menu represent only one of many possible payouts associated with the total return for the equity claim. For that reason, we perform the identical regression to those discussed above for our two alternative cash flow measures, cash dividends plus repurchases and earnings. First, we perform the same cross-sectional regressions using the 30 decile portfolios (10 size, 10 book-to-market, and 10 industry) detailed above. For dividend plus repurchases, $D_{2,t}$, and earnings, E_t, Table 4 (Panel B and C, respectively) document the ability of the estimated cash flow betas to explain the cross-section of average returns. For dividend plus repurchases, our results demonstrate that the estimated price of consumption risk is both positive and significant, but not for corporate earnings. The OLS estimate of λ_c is 0.072 for $D_{2,t}$ and 0.011 for E_t, with a HAC-adjusted t-statistic of 2.77 and 1.57, respectively. The adjusted R^2's are 29% and 9.3%, respectively, lower than what we document for the cash dividend betas. A non-trivial amount of cross-sectional variation is explained by the cash flow betas for dividends plus repurchases, but the cross-sectional explanatory power of the estimated cash flow beta is limited for earnings.

Recall, however, that the cash flow beta is a weighted average of the long-run cash flow exposure to consumption and the high-frequency contemporaneous relationship between cash flow and consumption shocks. If the latter is measured with considerable error, as it certainly is for the volatile corporate earnings (and likely $D_{1,t}$ and $D_{2,t}$), the risk detection problem is more challenging empirically. For cash dividends, we observe that the long-run risk exposure, γ_i, is the key empirical component in the cash flow beta. Since, it is also likely that the long-run exposure is less sensitive to high-frequency measurement and management problems, we explore this further, performing the same alternative cross-sectional regressions for $D_{2,t}$ and E_t. The results of these regression are presented in Panel B of Table 4, respectively. First, the estimated "prices of risk" associated with the long-run exposures, γ_i, are both positive and highly significant, with a cross-sectional $\bar{R}^2$ of 42% for dividends plus repurchases and 27% for earnings. As before, we also consider the joint regression of average returns on both γ_i and b_i, estimated for our two alternative cash flow measures. For both $D_{2,t}$ and E_t, the risk prices associated with the long-run exposure continue to be both positive and highly significant across both cases, whereas the risk prices on the contemporaneous covariance are negative, but statistically insignificant. The inconsistency across cash flow measures in the contemporaneous measures highlights the difficulties associated with detecting risk at high-frequencies, particularly in the presence of significant measurement and management issues. The detection problem is particularly acute for our measure of earnings growth. In sharp contrast, this evidence suggests that the exposure to *long-run* consumption risk, captured by γ_i, is an extremely robust quantity, with considerable ability to explain the observed cross-sectional patterns in average returns across all our candidate measures for equity cash flows.

5 Economic Motivations

In this section, we explore the implications of extending the equilibrium model to facilitate more general preference specifications. In particular, for the time-nonseparable preferences developed in Epstein and Zin (1989) (EZ), the Intertemporal Marginal Rate of Substitution (IMRS) is

$$M_{t+1} = \exp\{\theta \ln \delta - \frac{\theta}{\psi} g_{c,t+1} - (1-\theta) r_{c,t+1}\}. \tag{21}$$

$g_{c,t+1}$ is the growth rate (in logs) of consumption and $r_{c,t+1}$ is the return (in logs) on an asset that pays off aggregate consumption each period. Further, δ is a time preference parameter and ψ the intertemporal elasticity of substitution. The parameter, $\theta \equiv \frac{1-\alpha}{1-\frac{1}{\psi}}$, wherein α represents the coefficient of relative risk aversion. Under this parameterization, the innovation in the (log) IMRS in this model is determined by

$$\eta_{m,t} = -\frac{1-\alpha}{\psi - 1}\eta_{c,t} - \frac{\psi\alpha - 1}{\psi - 1}\eta_{r_c,t} \tag{22}$$

where the innovation in the return on the consumption asset is $\eta_{r_c,t}$ and $\eta_{c,t}$ is the innovation in consumption growth. It is well recognized that the innovation to the return to the consumption stream, $\eta_{r_c,t}$, is endogenous to the model. For example, when consumption growth is assumed to be an AR(1) process with Gaussian innovations, equation (22) leads to a single-factor risk premium specification–we refer to this as Model 1. In Model 1, $\eta_{r_c,t}$ is a scalar multiple of the consumption innovation (i.e, perfectly correlated with consumption innovations) and as shown below, the cash flow beta is sufficient to characterize risk premia across assets. An alternative model (called Model 2) that leads to a two-factor specification follows where consumption dynamics are also characterized by stochastic volatility. In this case, expected returns may be time varying. Further, we have a two-factor model and the average return on assets is also determined by the covariation with $\eta_{r_c,t}$. This model captures the intuition that the risk premia on different assets are determined by the risk associated with the cash flow beta and the exposure of assets to a factor that determines time-varying risks.

5.1 Model 1: Constant Risk Premia

In the first model, we derive implications for risk premia in an economy where the risk premia on all assets are constant. As in equation (4), consumption growth follows an AR process with lag length 1:

$$g_{c,t+1} = \mu_c + \rho_c g_t + \eta_{c,t+1}$$

In this case, the innovation to the consumption portfolio is

$$\eta_{r_c,t} = (1 + b_c)\eta_{c,t},$$

where $b_c = \frac{1-\psi^{-1}}{1-\kappa\rho_c}$. Substituting this expression into equation (22) implies that

$$\eta_{m,t} = \lambda_1 \eta_{c,t},$$

where $\lambda_1 = \alpha + b_c \frac{\psi\alpha - 1}{\psi - 1}$. When consumption is assumed to be $i.i.d$, then $b_c = 0$ and λ_1 equals the risk aversion parameter α. Note that the return innovation to the consumption stream, $\eta_{r_c,t}$, is perfectly correlated with the innovations in consumption. These assumptions lead to a single-factor model with constant risk premia. The single factor prices risks associated with consumption news.

With constant cost of capital, it is also straightforward to show that for any asset i, the return innovation is:

$$r_{i,t} - E_{t-1}[r_{i,t}] \equiv e_{r_i,t} = \beta_{i,d}\eta_{c,t} + \zeta_{i,t} \tag{23}$$

where, as before, the term $\beta_{i,d}\eta_{c,t} + \zeta_{i,t}$ represents news about cash flows. The arithmetic risk premium on any asset, approximately, is determined by $cov_t(\lambda_1\eta_{c,t+1}, e_{r_i,t+1})$, hence the risk premium is

$$E_t[R_{i,t+1} - R_{f,t+1}] = \beta_{i,d}\lambda_1 Var(\eta_{c,t}) \tag{24}$$

In this model, the cross-sectional differences in risk premia are determined by the differences in the long-run exposure of cash flows to consumption news.

The cross-sectional implications in equation (24) motivate the set of cross-sectional restrictions that we have explored in the previous section. Under these assumptions, the long-run exposure of cash flows to consumption news may be modeled using a VAR for cash flow and consumption growth. The resulting restriction on cross-sectional risk premia is

$$E[R_{i,t+1}] = \lambda_0 + \beta_{i,d}\lambda_c \tag{25}$$

which follows from equation (24), with the average risk free rate being λ_0 and the price of risk for consumption $\lambda_1 Var(\eta_c)$ being λ_c. Consequently, under this set of assumptions, risk premia in the cross section are driven only by the price of risk associated with risk inherent in aggregate consumption growth.

5.2 Model 2: Risk and Return with Time-Varying Risk Premia

To allow for the possibility that risk premia are time-varying, we begin by assuming that consumption growth innovations are characterized by stochastic volatility. In this setting, the innovation in the return to the consumption stream is given by

$$\eta_{r_c,t} = b_1\eta_{c,t} + \sum_K b_k\eta_{k,t}$$

The terms $\eta_{k,t}$ correspond to the innovations in risk premia—for simplicity we assume that all the risk sources are uncorrelated. This can be motivated by a model that captures fluctuating consumption volatility as in Bansal and Yaron (2002) or can simply be viewed as a version of the ICAPM in Merton (1973). The innovations to the returns on the consumption stream are not perfectly correlated with consumption innovations as in Model 1.

Consider the innovation in the return to any asset i, where the risk premium on the asset varies:

$$r_{i,t} - E_{t-1}[r_{i,t}] \equiv e_{r_i,t} = \beta_{i,d}\eta_{c,t} + \zeta_{i,t} - \sum_k \beta_{i,k}\eta_{k,t} \tag{26}$$

In addition to cash flow news, changes in expected returns also affect the return innovations. Consider the covariation in return innovations with innovations in the pricing kernel, $cov_t(\frac{1-\alpha}{\psi-1}\eta_{c,t} + \frac{\psi\alpha-1}{\psi-1}\eta_{r_c,t}, e_{r_i,t})$. Given our assumptions above, this covariation implies that the risk premium can be (approximately) stated as

$$E_t[R_{i,t+1} - R_{f,t+1}] = \beta_{i,d}\lambda_1 Var_t(\eta_{c,t}) + \sum_k \beta_{i,k}\lambda_k Var_t(\eta_{c,t}) \tag{27}$$

Economically, equation (27) captures the intuition that risk premia on assets are determined by the cash flow beta and by variables that may influence the expected returns.

This model also allows us to interpret the links between market betas and expected returns. Note that the market return innovation will also satisfy equation (26). Hence, the covariance between return innovations to an asset i and the market is

$$\beta_{i,d}\beta_{mk,d} var(\eta_c) + \sum_k \beta_{i,k}\beta_{mk,k} var(\eta_k) \tag{28}$$

Note that across assets this covariance is a weighted average reflecting all risks: the cash flow risk, $\beta_{i,d}$, and risks associated with expected return news. The market beta of an asset will also reflect a weighted average of these two individual betas. However, while each individual beta may be important (and significantly priced), a weighted average of the two betas may fail to appear to be a priced risk source, as each beta carries different prices of risks (see equation (27)). This is one potential reason why market betas may fail to explain the cross-section of average returns.

One way to evaluate this proposition is to consider a regression of the market betas on the cash flow betas. This regression provides a sense of how much of the market beta is driven by the cash flow beta. Since the residual from this projection would only approximately identify the weighted average term $\sum_L \beta_{i,L} var(\eta_l)$, it may not be useful in explaining risk premia across assets. That is, the portion of market beta that is orthogonal to cash flow beta may be insufficient to capture risk attributable to aggregate economic uncertainty. However, as we are able to identify $\beta_{i,d}$ separately, we can still infer the percentage of the cross-section of market betas that are driven by the cash flow betas.

5.3 Multi Factor Model: Estimation and Empirical Results

To consider the implications of the addition of the market beta to the cross-sectional explanatory power of the cash flow beta, we first must obtain a time-series estimate of the usual market beta. To do this, we augment the set of orthogonality conditions to include

$$E[(r_{i,t} - \bar{r}_{i,t})(r_{m,t} - \bar{r}_m)] = 0 \tag{29}$$

where, to maintain parsimony in estimation as above, we also demean all returns and market betas are estimated asset-by-asset. In addition, we also consider the modified cross-sectional restrictions

$$R_{i,t} = \lambda_0 + \lambda_1 \gamma_i + \lambda_2 b_i + \lambda_m \beta_{i,m} + e_{i,t} \tag{30}$$

Given the evidence presented above, we explore the separate effects of $\beta_{i,m}$, γ_i and b_i for the all three candidate measures of cash flows. All standard errors for the prices of risk are, as before, HAC-adjusted.

In Table 5 (Panel A), we report the time-series estimates of the market betas (see equation (29)). As can be seen, the market betas, $\beta_{i,m}$, are estimated in the time-series with precision. Additionally, it appears that the market betas across the market capitalization sorted portfolios exhibit a strong pattern in accordance with their observed average returns (a well-known result), but this is not true for the book-to-market sorted portfolios; the high and low book-to-market portfolios have very similar estimates of the market beta. The industry sorted portfolios display a less pronounced pattern, but the durable goods industry is associated with the largest market beta and does display the largest average return. In the cross-section, however, the estimated market price of risk, λ_m, is not significant, and the adjusted R^2 is only 4%.

In Table 5 (Panel B), the results for the multi-factor specification are presented. As can be seen, the inclusion of the market beta into the cross-sectional regressions, does not dramatically affect the explanatory power of the long-run exposure, γ_i. Estimated risk-prices for the market beta are not statistically different from zero in any case. For example, for the cash dividend measure, the estimated risk price associated with the market portfolio covariance, λ_m, is 0.12, but with a HAC adjusted t-statistic of only 0.14. Conversely, the estimated risk price for the long-run cash dividend exposure, γ_i, with respect to consumption is 0.09, with a HAC adjusted standard error of 2.81. The adjusted R^2 is 0.51, nearly identical to the R^2 observed above. This patterns are consistent across all three cash flow measures. Additionally, in no case is the contemporaneous covariance between cash flow and consumption shocks, b_i priced, as documented above. Taken together, the evidence that the usual CAPM market beta, a weighted average of an asset's exposure to multiple sources of risk, does not do a particularly good job explaining the cross-section of observed returns is not particularly surprising. However, from the perspective of our model, the pronounced cross-sectional variation in exposure to long-run consumption risk is uniform across various candidate measures of portfolio cash flow. Further, as these exposures correspond to the observed average returns, the documented risk premia spreads across these portfolios does not appear to be particularly puzzling.

5.4 Long-run Aggregate Risk Factor Analysis

This paper differs from standard practice in the asset pricing literature in that risk measures are obtained by estimating covariances between cash flow measures and aggregate sources of risk. In contrast, the standard pricing framework retrieves risk measures from the covariance of *returns* with these sources of risk. In this section, we provide an analysis of the information contained in both the cash flow streams and the price appreciation of the portfolio for the cross section of returns. In particular, we examine a factor portfolio that captures the information in our cash flow risk measures, similar to practice in the asset pricing literature.

We first construct a long-run aggregate risk factor mimicking portfolio, $R_{\gamma,t+1}$, by weighting returns by the second column of

$$\omega = \left(\left(\gamma' \gamma\right)^{-1} \gamma' \right)' \tag{31}$$

where γ represents the vector of estimated long-run risk exposures, γ_i, presented above for cash dividends and dividends plus repurchases. We exclude earnings from this exercise given the shorter time span for which earnings data are available. Factor loadings for each of the 30 size, book-to-market and industry portfolios are calculated via time series regressions as follows:

$$R_{i,t+1} = \alpha_i + \beta_{i,\gamma} R_{\gamma,t+1} + \epsilon_{i,t+1} \tag{32}$$

The remaining models are obtained by regressing returns on the value-weighted market (CAPM), the per capita growth in consumption of nondurables and services (CCAPM), and the Fama-French risk factors (FF).

In Table 6 (Panel A), we present cross-sectional regressions of average returns for the 30 size, book-to-market and industry portfolios on alternative factor beta specifications.

First, measured exposures to our long-run risk factor mimicking portfolio do a very good job of explaining the observed cross-sectional variation in average returns. For example, the estimated prices of long-run aggregate factor risk are 0.796 (based upon the cash dividend sort, $D_{1,t}$) and 0.805 (based upon the dividend plus repurchases sort, $D_{2,t}$), and are both highly significant. Further, the cross-sectional $\bar{R}^2$'s associated with each factor are 56% and 71%, respectively. Figure 3 presents a plot of the estimated γ_i using the cash flow measure $D_{1,t}$ against the factor mimicking portfolio loadings. As shown by the plot, the two risk measures display a strong positive relationship; the correlation between the two series is 0.74. Our long-run risk factor compares favorably with alternative factor based models. The CAPM and C-CAPM factors capture only 17% and 32%, respectively, of the variation in average returns. The three-factor Fama French model performs much better, with an $\bar{R}^2$ of 67%. Interestingly, correlations between the three Fama-French factors and the long-run risk factor mimicking portfolios are quite high. The correlation between the long-run risk factor portfolio measured with $D_{1,t}$ and SMB_t is 0.75, whereas the correlation between the long-run risk factor portfolio measured with $D_{2,t}$ and HML_t is 0.56. This evidence suggests that the FF factors may actually be sorting along long-run economic risk.

6 Conclusion

This paper documents a striking empirical observation. The long-run cash flow exposures to aggregate consumption shocks across assets can explain a significant component of the cross-sectional variation in observed average returns across a challenging collection of size, book-to-market, and industry sorted portfolios. We measure cash flow betas by estimating the joint time-series dynamics for both aggregate consumption and portfolio specific cash flow growth rates using a VAR; however, we find that the *long-run* cash flow exposure implied by this specification is the key determinant of risk for all cash flow measures. In fact, the cash flow beta is equivalent to this long-run exposure if we assume, that the contemporaneous relationship between cash flow and consumption growth is insignificant (as it appears to be empirically). This assumption may be appropriate due, for example, to excessive high-frequency measurement noise.

Finally, we describe a model which allows for time-variation in both expected consumption growth and aggregate uncertainty, for which each risk source will require a distinct price. Under this specification, it is not surprising that the usual market beta, as a weighted average of an asset's exposure to these potential sources of risk, does not do a particularly good job explaining the cross-section of observed returns. From the perspective of our cash flow beta model, the pronounced cross-sectional variation in average returns across these portfolios does not appear to be particularly puzzling. Our model captures the economic intuition that cash flows of different assets, however measured in practice, have different long-run exposures to fluctuations in aggregate consumption, and that this exposure has considerable capacity to explain differences in mean returns across assets.

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Table 1: Summary Statistics

	Returns		D1		D2			
Portfolio	Mean	Std.	Mean	Std.	Mean	Std.	Div. Yld.	Rep. Yld.
s1	0.0314	0.1258	0.0111	0.0616	0.0134	0.0814	0.56	0.25
s2	0.0299	0.1145	0.0098	0.0409	0.0105	0.0713	0.72	0.23
s3	0.0299	0.1098	0.0079	0.0363	0.0092	0.0548	0.80	0.22
s4	0.0296	0.1069	0.0065	0.0376	0.0082	0.0712	0.84	0.23
s5	0.0294	0.1010	0.0069	0.0368	0.0089	0.0535	0.87	0.20
s6	0.0271	0.0961	0.0048	0.0306	0.0071	0.0555	0.90	0.21
s7	0.0273	0.0940	0.0056	0.0321	0.0076	0.0647	0.89	0.22
s8	0.0267	0.0910	0.0053	0.0540	0.0076	0.0711	0.92	0.21
s9	0.0253	0.0827	0.0047	0.0364	0.0058	0.0625	0.97	0.20
s10	0.0227	0.0766	0.0028	0.0209	0.0040	0.0481	0.93	0.16
b1	0.0225	0.0967	0.0025	0.0427	0.0043	0.0860	0.58	0.13
b2	0.0244	0.0875	0.0047	0.0536	0.0070	0.0705	0.77	0.13
b3	0.0235	0.0849	0.0035	0.0641	0.0051	0.0769	0.88	0.17
b4	0.0221	0.0826	0.0044	0.0615	0.0048	0.0891	0.94	0.22
b5	0.0286	0.0762	0.0092	0.0435	0.0104	0.0873	1.06	0.21
b6	0.0262	0.0764	0.0064	0.0344	0.0089	0.0548	1.10	0.19
b7	0.0279	0.0783	0.0067	0.0411	0.0082	0.0629	1.18	0.20
b8	0.0319	0.0793	0.0112	0.0379	0.0118	0.0600	1.22	0.19
b9	0.0320	0.0830	0.0091	0.0468	0.0095	0.0694	1.22	0.20
b10	0.0376	0.0974	0.0136	0.0794	0.0189	0.1320	1.10	0.31
i1	0.0255	0.0845	0.0073	0.0457	0.0077	0.0609	0.87	0.24
i2	0.0287	0.1039	0.0054	0.0634	0.0059	0.1012	1.12	0.17
i3	0.0222	0.0926	0.0014	0.0515	0.0035	0.0651	0.88	0.19
i4	0.0255	0.0840	0.0068	0.0304	0.0069	0.0803	1.01	0.21
i5	0.0260	0.1098	-0.0011	0.0445	0.0045	0.0879	0.62	0.19
i6	0.0219	0.0801	-0.0006	0.0331	0.0030	0.0836	1.14	0.12
i7	0.0255	0.1012	0.0011	0.0580	0.0039	0.0904	0.72	0.18
i8	0.0267	0.0859	0.0085	0.0281	0.0088	0.0826	0.77	0.18
i9	0.0204	0.0697	0.0011	0.0129	0.0010	0.0348	1.50	0.09
i10	0.0266	0.0905	0.0072	0.0316	0.0082	0.0555	0.95	0.20

Table 1 presents summary statistics for the data used in the paper. The table presents real mean returns and cash flow growth rates for a set of 30 portfolios. Portfolios are sorted into deciles on the basis of market capitalization (s1-s10), book-to-market (b1-b10), and ten industry groups (i1-i10). Summary statistics for two measures of cash flow growth, D1, the growth rate in dividends paid and D2, the growth rate in dividends plus repurchases, are presented. The final columns depict the average dividend and repurchase yields for the portfolios. Data are sampled at the quarterly frequency over the period 1949.2 through 2001.4 and are converted to real using the PCE deflator.

Table 2: Summary Statistics: Earnings

	Earnings		Returns	
Portfolio	Mean	Std.	Mean	Std.
s1	0.0550	0.4950	0.0286	0.1436
s2	0.0204	0.2001	0.0273	0.1293
s3	0.0176	0.0939	0.0271	0.1208
s4	0.0032	0.1532	0.0263	0.1176
s5	0.0144	0.0624	0.0270	0.1110
s6	0.0100	0.0796	0.0225	0.1052
s7	0.0103	0.0612	0.0237	0.1030
s8	0.0086	0.0518	0.0227	0.0991
s9	0.0118	0.0481	0.0208	0.0898
s10	0.0086	0.0374	0.0176	0.0811
b1	0.0092	0.0868	0.0166	0.1039
b2	0.0178	0.0936	0.0193	0.0936
b3	0.0088	0.0973	0.0202	0.0902
b4	0.0145	0.1023	0.0201	0.0893
b5	0.0164	0.1211	0.0193	0.0785
b6	0.0125	0.1272	0.0234	0.0801
b7	0.0114	0.0965	0.0248	0.0826
b8	0.0164	0.1408	0.0263	0.0819
b9	0.0228	0.1249	0.0296	0.0910
b10	-0.0338	0.6339	0.0362	0.1049
i1	0.0151	0.0606	0.0244	0.0940
i2	0.0101	0.0786	0.0190	0.1064
i3	0.0064	0.0602	0.0202	0.0849
i4	0.0097	0.0471	0.0227	0.0893
i5	-0.0055	0.1413	0.0188	0.1100
i6	0.0353	0.3276	0.0191	0.0894
i7	0.0085	0.0296	0.0148	0.0772
i8	0.0194	0.0692	0.0250	0.1258
i9	0.0516	0.1306	0.0237	0.0996
i10	0.0217	0.1044	0.0140	0.1061

Table 2 presents summary statistics for the earnings data used in the paper. The table presents the mean and standard deviation of arithmetic growth rates in earnings for a set of 30 portfolios. Portfolios are sorted into deciles on the basis of market capitalization (s1-s10), book-to-market (b1-b10), and ten industry groups (i1-i10). Data are sampled at the quarterly frequency over the period 1965.2 through 2001.4 and are converted to real using the PCE deflator.

Table 3: Time Series Parameters

	γ	SE	$\sum_{l=1}^{8}\kappa_{i,1}^{l}\rho_{l,i}$	SE	b_i	SE	$\beta_{i,d}$	SE
s1	1.7600	(2.1200)	0.6390	(0.0892)	0.8510	(0.6080)	2.6500	(1.8400)
s2	4.2960	(1.6320)	0.6090	(0.0923)	1.1800	(0.4820)	3.7100	(1.6400)
s3	2.1200	(1.2800)	0.5680	(0.1370)	0.9400	(0.5230)	2.5300	(1.4500)
s4	2.4240	(1.1360)	0.3150	(0.1270)	0.0135	(0.3760)	0.4200	(0.6130)
s5	1.7760	(1.1440)	0.4030	(0.1180)	0.0467	(0.3710)	0.3710	(0.6300)
s6	2.4400	(0.8400)	0.4460	(0.1010)	0.6500	(0.3300)	1.5800	(0.6530)
s7	1.7680	(1.1200)	0.1910	(0.1950)	-0.3230	(0.4090)	-0.1080	(0.4990)
s8	1.8400	(1.1840)	0.1880	(0.2000)	1.1200	(0.5280)	1.6900	(0.6650)
s9	1.3360	(0.7768)	0.3370	(0.1330)	0.4970	(0.2620)	0.9700	(0.4210)
s10	0.0896	(0.7024)	0.2320	(0.1420)	0.5740	(0.2600)	0.7630	(0.3990)
b1	1.2720	(2.3840)	0.4480	(0.1230)	0.8390	(0.4520)	1.7300	(1.1800)
b2	-3.3680	(1.7200)	0.4200	(0.1210)	0.5120	(0.6310)	0.3260	(1.2000)
b3	0.4240	(1.8640)	-0.0172	(0.1340)	0.7300	(0.6770)	0.7880	(0.7310)
b4	-0.5544	(2.0560)	0.5240	(0.1420)	-0.6550	(0.6350)	-1.4700	(1.5400)
b5	0.4680	(1.5120)	0.4500	(0.1420)	-0.3350	(0.4240)	-0.5310	(0.8370)
b6	1.6960	(1.2160)	0.5330	(0.1280)	0.4010	(0.3710)	1.1400	(0.9620)
b7	1.7760	(1.0720)	0.0831	(0.1830)	0.7130	(0.6260)	1.0700	(0.5920)
b8	3.6080	(1.2560)	0.4800	(0.1160)	0.7830	(0.3780)	2.1000	(0.8670)
b9	4.0800	(1.9440)	0.4910	(0.1740)	0.4110	(0.5510)	1.4800	(1.3600)
b10	8.4800	(2.7280)	0.5060	(0.1680)	1.7900	(0.8020)	5.0200	(1.8700)
i1	0.2464	(0.9680)	0.5550	(0.1890)	-0.1300	(0.3630)	-0.2520	(0.8560)
i2	3.0640	(2.4320)	0.0578	(0.1340)	2.2500	(0.7850)	2.9000	(1.1000)
i3	2.7760	(1.0800)	-0.1170	(0.1550)	0.4310	(0.4250)	0.8450	(0.4410)
i4	-0.2528	(0.8000)	0.3800	(0.1470)	-0.1470	(0.2930)	-0.2800	(0.5170)
i5	2.9200	(0.9360)	0.1670	(0.1400)	0.2310	(0.3700)	0.7600	(0.5300)
i6	-0.3128	(0.7136)	0.1100	(0.1470)	-0.0364	(0.3780)	-0.0926	(0.5030)
i7	2.0880	(1.2960)	0.1190	(0.2240)	-0.3520	(0.4070)	-0.0537	(0.4320)
i8	-0.5896	(0.7120)	0.0468	(0.1540)	0.5240	(0.2870)	0.4520	(0.3030)
i9	-0.3032	(0.5752)	0.6120	(0.0705)	0.6950	(0.1160)	1.7400	(0.3930)
i10	0.6432	(0.8320)	0.1260	(0.1760)	0.7790	(0.3940)	0.9980	(0.4910)

Table 3 depicts the estimated time series parameters from the model

$$\begin{aligned} g_{c,t+1} &= \rho_c g_{c,t} + \eta_{t+1} \\ g_{i,t+1} &= \gamma_i g_{c,t} + u_{i,t+1} \\ u_{i,t+1} &= b_i \eta_{t+1} + \sum_{l=1}^{8} \rho_{l,i} u_{i,t-l+1} + \zeta_{i,t+1} \\ \beta_{d,i} &= \frac{\kappa_{i,1}\gamma_i}{1-\kappa_{i,1}\rho_c} + \frac{b_i}{1-\sum_{l=1}^{8}\kappa_{i,1}^{l}\rho_{l,i}} \end{aligned}$$

where $g_{c,t+1}$ represents the demeaned growth rate in aggregate consumption and $g_{i,t+1}$ represents the demeaned growth rate in the dividends paid on portfolio i. The parameter $\kappa_{i,1}$ represents a constant of approximation in the Campbell and Shiller (1988) expression for returns. Data used in the estimation are 30 portfolios sorted on size, book-to-market and industry and are sampled quarterly over the period 1949.2 through 2001.4. All quantities are demeaned and converted to real using the PCE deflator. Standard errors are presented in parentheses and are estimated using a HAC covariance matrix with one Newey-West lag. Standard errors for $\sum_{l=1}^{8}\kappa_{i,1}^{l}\rho_{l,i}$ and $\beta_{d,i}$ are computed via the delta method.

Table 4: Cross-Sectional Regressions

Panel A: D1

		λ_0	λ_γ	λ_b	λ_c	$\bar{R}^2$
a)	Point Est.	2.450			0.079	0.532
	t-stat	4.730			2.410	
b)	Point Est.	2.470	0.101			0.527
	t-stat	4.760	2.480			
c)	Point Est.	2.460	0.092	0.044		0.522
	t-stat	4.750	2.590	0.915		

Distribution of t-statistics and $\bar{R}^2$

		2.5	5.0	10.0	20.0	30.0	40.0	50.0	60.0	70.0	80.0	90.0	95.0	97.5
a)	t-stat (λ_c)	-2.570	-2.380	-2.110	-1.700	-1.230	-0.681	0.017	0.673	1.240	1.720	2.140	2.410	2.600
	$\bar{R}^2$	-0.036	-0.035	-0.032	-0.021	-0.004	0.023	0.056	0.098	0.155	0.226	0.331	0.410	0.476
b)	t-stat (λ_γ)	-2.572	-2.368	-2.111	-1.700	-1.244	-0.714	-0.029	0.706	1.255	1.714	2.129	2.399	2.586
	$\bar{R}^2$	-0.035	-0.035	-0.032	-0.019	-0.001	0.026	0.061	0.108	0.164	0.239	0.348	0.430	0.488
c)	t-stat (λ_γ)	-2.529	-2.319	-2.044	-1.609	-1.151	-0.642	-0.013	0.613	1.161	1.637	2.062	2.340	2.557
	$\bar{R}^2$	-0.064	-0.053	-0.033	0.009	0.052	0.095	0.141	0.190	0.245	0.311	0.398	0.467	0.520

Panel B: Alternative Cash Flow Measures

	λ_0	λ_γ	λ_b	λ_c	$\bar{R}^2$
Point Est.	2.430			0.072	0.285
t-stat	4.690			2.770	
Point Est.	2.470	0.090			0.415
t-stat	4.650	3.180			
Point Est.	2.510	0.088	-0.031		0.404
t-stat	4.990	3.090	-0.564		

	λ_0	λ_γ	λ_b	λ_c	$\bar{R}^2$
Point Est.	2.210			0.011	0.093
t-stat	3.310			1.570	
Point Est.	2.080	0.029			0.265
t-stat	3.060	2.230			
Point Est.	2.070	0.030	0.004		0.255
t-stat	3.050	2.200	0.720		

Table 4 presents cross sectional regressions of average returns for 30 portfolios on the long-run beta, $\beta_{d,i}$ developed in the paper:

$$R_{i,t} = \lambda_0 + \lambda_c \beta_{d,i} + v_{i,t}$$

In Panel A, results are presented for cash dividends, $D_{1,t}$, covering the period 1949-2001; results with quarterly data over the period 1949:2-2001:4 for $D_{2,t}$ and 1965:2-2001:4 for E_t are presented in Panel B. Parameters are estimated via ordinary least squares (OLS); t-statistics are computed with HAC-adjusted standard errors. We also present the distribution of the t-statistics for the test $H_0 : \lambda_c = 0$ and the $\bar{R}^2$ generated by a Monte Carlo experiment of 10,000 replications. In the Monte Carlo, we simulate the demeaned consumption growth rate where $\hat{\rho}_c$ is the autoregressive using the AR(1) parameter and standard deviation of the residual in the data. Simulated consumption growth rates and observed dividend growth rates are used to generate the trailing moving sum of growth rates used in the estimation of γ_i, estimate the time series parameters in model (9) and the cross-sectional parameters in the above specification.

Table 5: Cross-Sectional Regressions

Panel A: Betas

	β_i	SE		β_i	SE		β_i	SE
s1	1.240	(0.066)	b1	1.110	(0.027)	i1	0.904	(0.062)
s2	1.230	(0.050)	b2	1.040	(0.025)	i2	1.110	(0.035)
s3	1.220	(0.047)	b3	1.010	(0.023)	i3	1.060	(0.033)
s4	1.200	(0.049)	b4	0.942	(0.034)	i4	0.737	(0.065)
s5	1.170	(0.033)	b5	0.868	(0.040)	i5	1.250	(0.052)
s6	1.120	(0.033)	b6	0.890	(0.030)	i6	0.750	(0.063)
s7	1.120	(0.026)	b7	0.887	(0.040)	i7	1.090	(0.060)
s8	1.090	(0.022)	b8	0.899	(0.046)	i8	0.933	(0.049)
s9	1.010	(0.014)	b9	0.903	(0.056)	i9	0.585	(0.054)
s10	0.931	(0.016)	b10	0.975	(0.074)	i10	1.020	(0.039)

Panel B: Cross-Sectional Regressions

CF Measure		λ_0	λ_γ	λ_b	λ_{mkt}	R^2
	Point Est.	2.100			0.580	0.038
	t-stat	2.860			0.670	
D1	Point Est.	2.340	0.090	0.043	0.121	0.507
	t-stat	3.280	2.810	0.931	0.146	
D2	Point Est.	1.860	0.085	-0.066	0.704	0.483
	t-stat	2.450	3.130	-1.670	0.806	
E	Point Est.	1.081	0.034	0.005	0.905	0.402
	t-stat	1.141	2.313	0.872	0.935	

Table 5 presents cross sectional regressions of average returns for 30 portfolios on the long-run beta, $\beta_{d,i}$ developed in the paper:

$$R_{i,t} = \lambda_0 + \lambda_c \beta_{d,i} + \lambda_\beta \beta_{mkt,i} + v_{i,t}$$

Panel A depicts GMM estimates of betas using quarterly real returns data. In Panel B, cross-sectional regression results are presented for various cash flow measures; data cover the period 1949-2001 in the case of D1 and D2 and 1965-2001 in the case of E. Parameters are estimated via ordinary least squares (OLS); t-statistics are computed with HAC-adjusted standard errors.

Table 6: Cross-Sectional Regressions: Alternative Specifications

	λ_0	λ_γ	$\lambda_{\beta_{i,c}}$	$\lambda_{\beta_{i,m}}$	λ_{MRP}	λ_{SMB}	λ_{HML}	$\bar{R}^2$
D1	1.038	0.796						0.564
	13.184	6.316						
D2	1.211	0.805						0.708
	26.580	8.589						
CCAPM	1.014		0.178					0.318
	8.111		3.876					
CAPM	1.055			0.930				0.168
	6.594			2.667				
FF	0.242				0.993	0.333	0.971	0.666
	0.530				2.159	3.195	5.432	

Table 6 presents cross-sectional regressions of average returns for 30 portfolios on alternative beta specifications. Betas for the models designated $D1$ and $D2$ are calculated via time series regression:

$$R_{i,t+1} = \alpha_i + \beta_{i,\gamma} R_{\gamma,t+1} + \epsilon_{i,t+1}$$

where $R_{\gamma,t+1}$ represents a factor mimicking portfolio constructed by weighting the returns by the second column of

$$\omega = \left(\left(\gamma'\gamma\right)^{-1} \gamma' \right)'$$

where γ represents the vector of in sample estimated γ_i above. The remaining models are obtained by regressing returns on the value-weighted market (CAPM), the per capita growth in consumption of nondurables and services (CCAPM), and the Fama-French risk factors (FF).

Figure 1: Aggregate Repurchases and Dividends

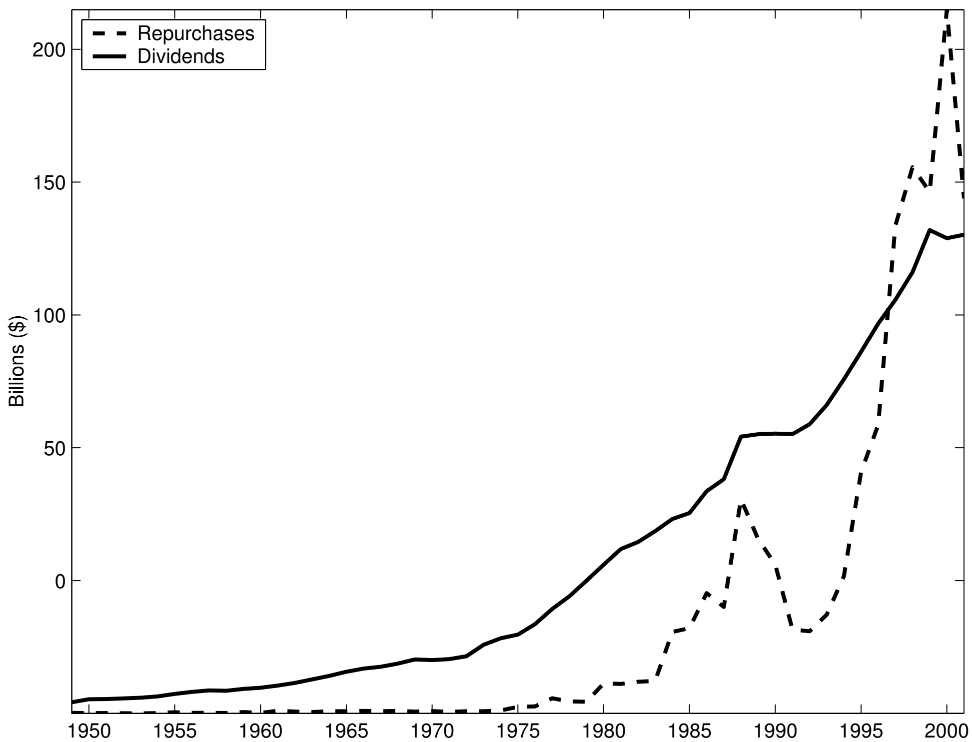
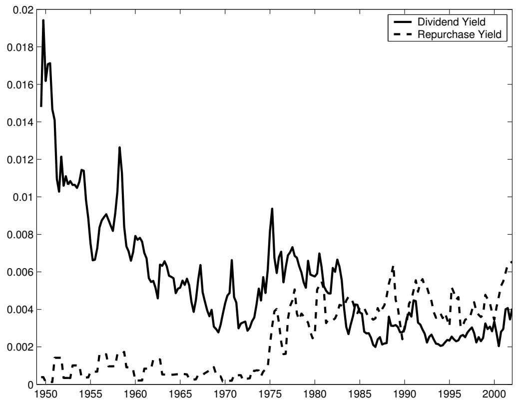


Figure 1 presents aggregate dividends and repurchases. Dividends are calculated as $D_{1,t+1} = y_{1,t+1}V_{1,t}$, where $y_{1,t+1}$ represents the dividend yield on the aggregate market at time $t+1$ and $V_{1,t}$ represents the entry value of the market. Repurchases are calculated by subtracting $D_{1,t+1}$ from the quantity $D_{2,t+1} = y_{2,t+1}V_{2,t}$, where $V_{2,t}$ represents the adjusted market value from:

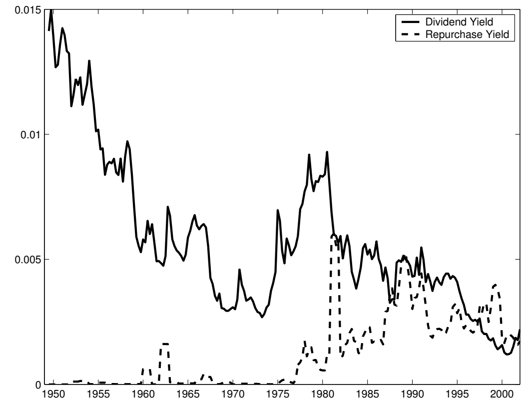
$$h_{2,t+1} = \frac{P_{t+1}}{P_t} \cdot \min\left[\frac{n_{t+1}}{n_t}, 1\right]$$

and $y_{2,t+1} = R_{t+1} - h_{2,t+1}$.

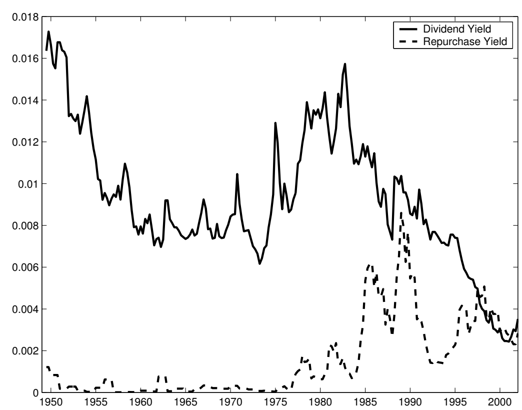
Figure 2: Cash Flow Yields by Characteristic



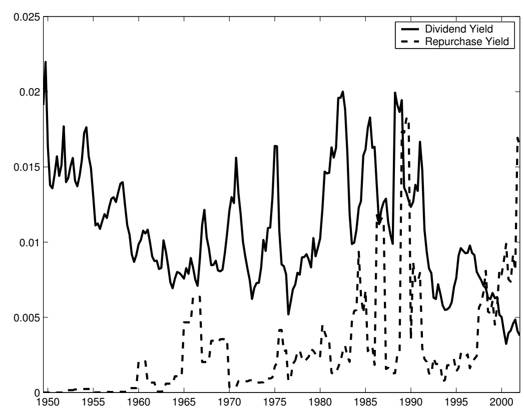
(a) Small



(b) Low B/M



(c) Large



(d) High B/M

Figure 2 presents yields for cash dividends and repurchases for portfolios sorted on the characteristics of size and book-to-market ratio. Panel A presents results for the small market capitalization portfolio, Panel B for the low book-to-market portfolio, Panel C for the large capitalization portfolio, and Panel D for the high book-to-market portfolio.

Figure 3: Scatterplot: γ_i vs. Factor Mimicking Portfolio Beta

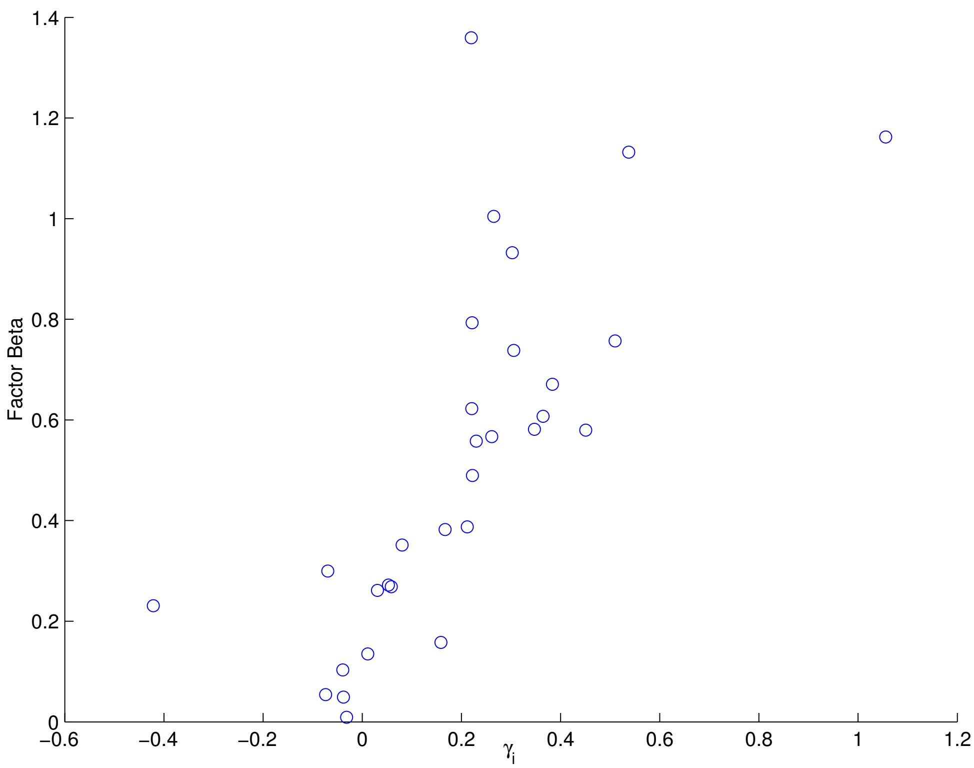


Figure 3 presents a scatterplot of the risk measures of the 30 portfolios used in the paper. The scatter plot represents a plot of γ_i against the factor loading, β_i for the portfolio. γ_i is estimated as a regression of the growth rate in the cash dividend series, $D_{1,t}$, on the trailing eight-quarter moving sum of aggregate consumption growth. β_i is estimated as the projection coefficient from a regression of the return on asset i on the $D_{1,t}$ factor mimicking portfolio.