Return Decomposition*

Long Chen
Department of Finance
Michigan State University
chen@bus.msu.edu
(517) 353-2955

Xinlei Zhao
Department of Finance
Kent State University
xzhao@kent.edu
(330) 672-1213

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Abstract

We study the robustness of the return decomposition approach, in which unexpected equity return is decomposed into discount rate (DR) news and cash flow (CF) news. In this approach, the discount rate news is directly modeled but the cash flow news is usually backed out as a residual component. We argue that the approach has serious limitations because the cash flow news, as a residual, depends critically on how successfully the discount rate news is modeled. A missing forecasting variable can change the balance of the two news components and the conclusions that compare the two parts. To illustrate this point, we apply the approach to Treasury bonds that should have zero CF variance and zero CF betas. In contrast, we find that the variance of the "CF news" is larger than that of the DR news; and that bonds with longer maturities have higher "CF betas." Applying the approach to equity returns, we show that (i) the relative importance of CF variance and DR variance of the market portfolio is sensitive to the choice of forecasting variables; and (ii) for most forecasting-variable specifications, value stocks usually do not have higher CF betas. These results run counter to what is reported using the decomposition approach in the current literature. We further decompose the CF news in the current literature into directly-modeled CF news and residual news; we show that opposite conclusions can be drawn depending on the nature of the residual news. We also reconcile our finding that value stocks do not have higher CF betas with the finding in a related litearture that value stocks have higher CF covariation with aggregate CFs. We finally provide a test that suggests an unresolved issue for research on DR risk and CF risk.

JEL Classification: G11, G12
Key Words: return decomposition, discount rate risk, cash flow risk, discount rate beta, cash flow beta, value stock, growth stock.

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1 Introduction

The seminal work by Campbell and Shiller (1988A) suggests that unexpected asset returns can be decomposed into two components: news about discount rates (DRs) and news about cash flows (CFs). Many subsequent studies follow this route and examine the relative importance of the two components in determining returns. Among them, one popular approach is to directly model the DR news and back out the CF news as the residual component. As Campbell and Vuolteenaho (2004A) argue, "This practice has an important advantage – one does not necessarily have to understand the short-run dynamics of dividends. Understanding the dynamics of expected returns is enough." We call this the *return decomposition approach* in the rest of the paper. Using this method, some important conclusions have been drawn:

- The variance of the DR news is much larger than the variance of the CF news for the market portfolio, and the magnitude of DR betas is larger than that of CF betas at portfolio level. The combined evidence has been cited to support the claim that equity returns at the aggregate level are mainly driven by the time-varying risk premium.

- In a recent influential paper, Campbell and Vuolteenaho (2004A) find that, during the 1963-2001 period, value stocks have higher CF betas but lower DR betas than growth stocks do. They conclude that (i) value stocks have higher equity returns than growth stocks because they have higher CF betas, and (ii) to calculate the cost of equity, the more important measure of risk is not the market beta, but the CF beta.

Despite the large number of articles published using this method and their important academic and practical implications – they always center on the DR risk and CF risk, the two fundamental components of asset valuation – we are not aware of a single study that fully examines the robustness of this approach. This paper makes the first attempt to fill this void.

We argue that the return decomposition approach has an important limitation: the CF news could very well be a catchall for modeling noise. The two news components have to sum up to the total unexpected return and thus, the CF news, as the residual, depends critically on how well the DR news is captured. A missing state variable in the DR forecasting equation will show up on the CF side and change the relative balance of the two news components. It can change the relative variances and cause cross-sectional biases if the missing state variable is priced cross-sectionally in asset returns. We provide a simple theoretical example to show that omitting state variables can lead to misleading cross-sectional patterns of the betas, in which the trends of the DR betas and

CF betas can be in opposite directions.

While model misspecification is always a potential problem any estimation faces, it is likely to be more damaging for the return decomposition approach. In a regular multifactor model, even if a factor is missing, we can still draw inferences about the specified factors despite increased noise, so long as the omitted factor is not correlated with the specified factors. In the return decomposition approach, because the major conclusions are drawn based on the comparison between the specified factors and the unspecified ones (i.e., the residual), the role of the missing factor could be crucial.

To illustrate this point, we first apply the decomposition approach to Treasury bond returns. The cash flows of these securities are fixed: real interest rate shocks and inflation shocks can only be channeled into the nominal interest rate and affect bond returns. Therefore, unexpected returns are driven solely by the DR risk because they have no nominal CF uncertainty; the estimated "CF news" contains no actual CF news but is pure modeling noise.[1] Treasury bonds thus provide a unique opportunity to separate true cash flow risk from the noise due to our limited ability to forecast DR. If the decomposition approach is proper, we expect that the variance of the DR news far exceeds the variance of the "CF news"; that the DR betas are much larger than the CF betas (which should be zero); and that, cross-sectionally, longer-maturity bonds have higher DR betas but there should be no dispersion of CF betas.

In stark contrast, we find that the estimated variance of the "CF news" is larger than that of the DR news, and that the CF betas are larger than the DR betas. In addition, longer-maturity bonds have *higher* CF betas but *lower* DR betas. Because we know the so called CF news is in fact DR news in disguise, the evidence suggests that missing state variables in the DR forecast can induce misleading patterns and cause us to draw wrong conclusions regarding (i) the relative variances, (ii) the relative magnitude of betas, and (iii) the cross-sectional patterns of betas.

We then apply the decomposition approach to equity returns. Because, unlike Treasury bonds, equities have both DR risk and CF risk, we cannot cleanly separate the CF risk from modeling noise. Nevertheless, we can still examine whether the results in the current literature are sensitive to the choice of state variables. Campbell and Vuolteenaho (2004A) use the term spread (difference between long-term and short-term bond yield), the 10-year smoothed price-earning (PE) ratio, and the value spread (log book-to-market of value stocks minus that of growth stocks), which we call

[1]Note in all previous studies in this literature CF news is always nominal. For equities inflation risk can be classified as both discount rate risk and cash flow risk because both the nominal discount rate and expected future cash flow can increase with inflation (see Campbell and Vuolteenaho (2004B)). For Treasury securities, however, inflation shocks can only affect the discount rate. Accordingly, nominal interest rate reflects expected inflation but nominal cash flows are fixed. When we apply the return decomposition according to bond present value formula there must be no cash flow risk.

the benchmark case. We find the following patterns related to the benchmark case.

First, the benchmark case is sensitive to close substitutes, to updates, or to sample periods. As Campbell and Vuolteenaho (2004A) point out, the impact of a state variable is a function of its persistence. The dominant variable in the benchmark case is the 10-year smoothed PE ratio with autocorrelation more than 0.99, which raises serious stationarity concerns. Because the PE ratio is meant to capture expected returns, we thus replace the 10-year PE ratio by close substitutes that perform similar roles, including (i) 1-year PE ratio, which is less smoothed; (ii) dividend yield, which is more commonly used to predict equity returns;[2] (iii) the Dow Jones book-to-market ratio (e.g., Kothari and Shanken (1997), Pontiff and Schall (1998), and Lewellen (1999)); (iv) the book-to-market spread (Liu and Zhang (2006)), whose inclusion makes the (dropped) 10-year PE ratio insignificant but other variables more significant, and thus improves the overall explanatory power. In all above cases we find that value stocks have lower CF betas. In addition, the 10-year smoothed PE ratio, which is from Shiller (2000), has been updated by Shiller. Once we replace the old PE ratio with the new one, value stocks have lower CF betas even for the same sample period as the benchmark case. Further, even if we do not update the 10-year PE ratio, once we apply the return decomposition to the postwar period (instead of the full 1929-2001 period) because CAPM breaks down in this period (see Ang and Chen (2005) and Fama and French (2005)), value stocks have lower CF betas.[3]

Second, the CF beta trend from growth to value stocks is sensitive to alternative model specifications. We only present two cases in the paper: (i) the state variables used in Petkova (2006) that can intuitively explain the Fama-French factors; and (ii) the inclusion of cay (Lettau and Ludvigson (2001A, 2001B)) and the risk premium factor and the volatility factor (Ludvigson and Ng (2005)) that can largely increase the predictive power of equity returns. In both cases we find that the CF beta trend either is reversed or disappears. We further explore the variables in Goyal and Welch (2006) that have perhaps the most recent comprehensive list of variables that predict equity returns. It is fair to say that for most combinations value stocks do not have higher CF betas.

Third, if it is true that the CF beta is an important measure for calculating the cost of equity, then we expect the CF beta to be priced in most portfolios. We use the state variable specification in the benchmark case and calculate the betas for the 48 Fama-French (1997) industry portfolios.

[2] Shiller (1984) and Fama and French (1988) find that dividend yield predicts equity return better than the earning price ratio does. Dividend yield (rather than PE ratio) is also used in many other studies related to the decomposition approach, including Campbell and Shiller (1988A), Campbell and Mei (1993), and Campbell and Vuolteenaho (2004B). See also Keim and Stambaugh (1986). Note the dividend yield is less persistent than the 10-year PE ratio is.

[3] Campbell and Vuolteenaho (2004A) emphasize that the inclusion of the value spread is crucial. Our evidence here suggests that the 10-year PE ratio is more important.

We find that the CF beta is indeed priced for these portfolios, but in just the wrong way: we would conclude that portfolios with higher CF betas should be assigned a lower cost of equity, which is inconsistent with the systematic risk interpretation.

Finally, the relative importance of the DR news and the CF news of the market portfolio varies in a fashion similar to the cross-sectional pattern of the betas, depending on what state variables are included. For example, with monthly data, the benchmark case leads to the conclusion that DR variance far exceeds the CF variance for the 1929-2001 period. Replacing the 10-year PE ratio by dividend yield leads to the finding that CF variance is slightly higher; replacing by the 1-year PE ratio leads to the finding that CF variance is slightly higher for the post-1952 period; replacing by the book-to-market spread, even though it improves the predictive power of equity return, leads to the finding that CF variance dominates for all periods.

A natural question is whether the results in the current literature are robust once we model both the CF news and the DR news directly. Such a procedure effectively separates the CF beta in the current decomposition approach into a direct CF beta and a residual beta. Given that dividend might be subject to corporate policies (Ang and Bekaert (2005)), we use two separate cash flow measures, dividend growth rate and earning return on equity, to calculate cash flow betas. Nevertheless, they give us identical inference: in the benchmark case, value stocks have both lower CF betas and lower DR betas, but higher residual betas. In other words, the results in the current literature are driven by the residual betas. Depending on whether the residual news represents CF news or DR news, opposite conclusions can be drawn, which further suggests the limitation of using this approach to draw meaningful conclusions.

We next reconcile our finding that value stocks do not have higher CF betas using the decomposition approach with the finding in a related cash flow literature that value stocks have higher CF covariations with consumption growth (e.g., Bansal, Dittmar, and Lunblad (2005) and Hansen, Heaton, and Li (2005)). Campbell and Vuolteenaho (2004A) are based on a model in which covariance between individual portfolio return and market CF news is assigned a higher price of risk than covariance between individual return and market DR news. Campbell and Vuolteenaho (2004A) thus decompose the market return into CF news and DR news but do not decompose individual portfolio returns. The cash flow literature does the opposite. It directly uses CF news of individual portfolios and uses market consumption growth news, which we show contains information regarding market return, and thus both CF news and DR news of the market. Therefore, the "CF news" in the two methods carry very different meanings, and thus it is not necessarily surprising to obtain different results.

We finally conduct a simple test that can shed light on the relative importance of CF news and DR news for both market and individual portfolios. The test is to see whether, as time horizon increases, value stocks gradually have higher long-term CAPM betas and consumption-CAPM betas. The intuition is that the cumulative impact of DR news will be washed out in the long run; in the limit, all risk is about CF risk (e.g., Hansen, Heaton, and Li (2005)). Because this test only uses returns and consumption growth, it has the advantage that it relies little on how DR news and CF news are modeled. We find that, from 1-year to 15-year horizons, the pattern that value stocks have significantly lower CAPM betas is stable; and value stocks do not have higher consumption-CAPM betas. Therefore, it is not clear that the lower CAPM betas of value stocks are DR related, as argued by Campbell and Vuolteenaho (2004A). Alternatively, if we accept the prior that value stocks have higher CF covariance with market cash flows that should matter in the long run, then we do not understand, in the context of CF risk and DR risk, the mechanism in the financial market (i.e., returns) that links short-run and long-rum risks.

When concluding, we emphasize that studies in the return decomposition literature usually conduct extensive robustness checks. Because they usually choose state variables based on their priors, only limited attention has been given to the sensitivity of these choices. For example, Campbell and Vuolteenaho (2004A) provide robustness checks for many aspects of their model. They also show that the results in the benchmark case continue to hold in several alternative specifications (reported in their online appendix). Instead, we reach a different conclusion because our prior is that the return decomposition approach must be sensitive to the choice of state variables. We provide a clear theoretical rationale on why this aspect of the robustness check could be vital. Our evidence supports this prior and suggests that serious caution needs to be exercised when interpreting the results from this approach.

The rest of the paper proceeds as follows: Section 2 provides theoretical discussions. Sections 3 and 4 examine Treasury bond returns and equity returns respectively based on the return decomposition approach. Section 5 studies direct cash flow measures and reconciles with the literature. Section 6 gives conclusions.

2 Theoretical discussion

2.1 Decomposition procedure

The idea that unexpected stock returns can be approximated by a linear combination of cash flow (CF) news and discount rate (DR) news dates back to Campbell and Shiller (1988A). Campbell

(1991) further provides the following decomposition of the unexpected return:

$$\begin{aligned} e_{t+1} &= r_{t+1} - \mathrm{E}_t r_{t+1} \\ &= (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= e_{CF,t+1} - e_{DR,t+1} \end{aligned} \tag{1}$$

where $r_{t+1}$is the equity return and E_t is the expectation operator at time t, ρ is a constant close to but lower than 1, and Δd_t is the dividend growth rate. We decompose the market portfolio following Campbell and Vuolteenaho (2004A). Thus, e_{t+1} is the unexpected market return, and $e_{CF,t+1}$ and $-e_{DR,t+1}$ are its CF news and DR news components.

For ease of presentation we suppress the time subscript when possible. The market beta is defined as

$$\beta_i = \frac{Cov\,(e_i, e)}{Var\,(e)}, \tag{2}$$

where e_i is the return of asset i. It can be further decomposed into two parts:

$$\begin{aligned} \beta_i &= \frac{Cov\,(e_i, e_{CF})}{Var\,(e)} + \frac{Cov\,(e_i, -e_{DR})}{Var\,(e)} & (3) \\ &= \beta_{i,CF} + \beta_{i,DR}, & (4) \end{aligned}$$

where $\beta_{i,CF}$ and $\beta_{i,CF}$ are, respectively, the CF beta and DR beta for asset i.

In order to decompose the unexpected return of the market portfolio, Campbell and Vuolteenaho (2004A) assume that a vector of state variables, z_{t+1}, evolves according to a first-order VAR (suppressing the constant):

$$z_{t+1} = \Gamma z_t + u_{t+1} \tag{5}$$

with the equity return as its first element. It then follows that the negative of the DR news is

$$\begin{aligned} e_{DR,t+1} &= (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= e1' \sum_{j=1}^{\infty} \rho^j \Gamma^{j+1} u_{t+1} \\ &= e1' \rho \Gamma \left(I - \rho\Gamma\right)^{-1} u_{t+1} \\ &= e1' \lambda u_{t+1}, \end{aligned} \tag{6}$$

where $\lambda = \rho\Gamma \left(I - \rho\Gamma\right)^{-1}$, and $e1$ is a vector whose first element is equal to one and zero otherwise. The idea is that, because the expected return is predictable (through the VAR system), any surprise in the current state variables will be incorporated into the expected return for every future period.

The cash flow news can then be backed out as the difference between the total unexpected return and the DR news:

$$e_{CF,t+1} = \left(e1' + e1'\lambda\right) u_{t+1}. \tag{7}$$

It follows that

$$\beta_{i,CF} \equiv \left(e1' + e1'\lambda\right) \frac{Cov\left(e_{i,t}, u_t\right)}{Var\left(e\right)}, \tag{8}$$

$$\beta_{i,DR} \equiv -e1'\lambda \frac{Cov\left(e_{i,t}, u_t\right)}{Var\left(e\right)}, \tag{9}$$

where $Cov\left(e_{i,t}, u_t\right)$ is a vector of covariance between firm i's stock return and the innovations in the state variables.

Following Campbell and Vuolteenaho (2004A), two adjustments are made in actual calculation. First, we use excess returns in the VAR system and the calculation of betas. Second, we include one lag of the market news when calculating the betas in order to mitigate the stale-price problem (e.g., Scholes and Williams (1977) and Dimson (1979)).

2.2 An ICAPM interpretation

Campbell (1993) derives an approximate discrete-time version of Merton's (1973) intertemporal CAPM. Based on that, Campbell and Vuolteenaho (2004A) show that

$$\mathrm{E}_t\left[r_{i,t+1}\right] - r_{f,t+1} = \gamma\sigma_M^2\beta_{i,CF} + \sigma_M^2\beta_{i,DR}, \tag{10}$$

where $r_{i,t+1}$ is the return for asset i, $r_{f,t+1}$ is the riskfree rate, σ_M^2 is the variance of the market portfolio, and γ is the risk-aversion coefficient. The above equation suggests that a conservative investor (with $\gamma > 1$) demands a higher expected risk premium on the CF beta than on the DR beta. Current theoretical models that study the equity premium puzzle usually assume that γ is larger than one (e.g., γ is between 7.5 and 10 in Bansal and Yaron (2004)). For this reason, Campbell and Vuolteenaho (2004A) call the CF beta the "bad beta" and the DR beta the "good beta". The intuition is that a positive unexpected market equity return, if DR related, implies lower future growth opportunities (i.e., lower returns). If a stock has a positive DR beta, meaning that the stocks pays more when the market's expected future growth opportunity shrinks, it is welcomed by conservative investors and thus less penalized. One model restriction is that the ratio of the coefficient of the CF beta and of the DR beta is equal to γ, the risk-aversion parameter.

2.3 Implications

We can integrate the VAR system into the equation above to obtain

$$\mathrm{E}_t\left[r_{i,t+1}\right] - r_{f,t+1} = \left(\gamma\sigma_M^2\left(e1' + e1'\lambda\right) + \sigma_M^2\left(-e1'\lambda\right)\right)\frac{Cov\left(r_{i,t}, u_t\right)}{Var\left(e_m\right)}. \tag{11}$$

The equation indicates that the researcher has the discretion to choose a vector u_t of state variables (factors). The rationale for the choice of any particular factor must come from sources outside of the model. In other words, the approach can only tell whether a particular factor has explanatory power, but is silent on why it matters.[4] The approach does differ from a regular multifactor model in the sense that no matter how many state variables are chosen, they must be combined into two components (i.e., the CF beta and the DR beta).

Because the CF news is backed out as the difference between the total return news and the DR news, it is inevitably affected by how the DR is modeled. In the following simple example we show that omitting stable variables can induce false cross-sectional patterns of CF betas and DR betas.

An example We assume that $z_t = [r_{m,t}\ x_t]'$, where $r_{m,t}$ is the market return and x_t is a certain state variable that explains the equity return, and the VAR system is

$$\begin{bmatrix} r_{m,t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} \alpha_1 & \alpha_2 \\ 0 & b_1 \end{bmatrix}\begin{bmatrix} r_{m,t} \\ x_t \end{bmatrix} + \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix}. \tag{12}$$

The system says that the market return is predicted by two state variables: the past return and x, and x is predictable only by its own lag. $u_{1,t+1}$ and $u_{2,t+1}$ are innovations in the return and x respectively. For simplicity, we also assume that $cov\left(e_{i,t}, u_{2,t}\right) = 0$. Then it can be easily shown that

$$\beta_{i,DR} = -\frac{\rho\alpha_1}{1-\rho\alpha_1} \times \frac{cov\left(e_{i,t}, u_{1,t}\right)}{var\left(u_{1,t}\right)} \tag{13}$$

$$\begin{aligned} \beta_{i,CF} &= \frac{cov\left(e_{i,t}, u_{1,t}\right)}{var\left(u_{1,t}\right)} - \beta_{i,DR} \\ &= \frac{1}{1-\rho\alpha_1} \times \frac{cov\left(e_{i,t}, u_{1,t}\right)}{var\left(u_{1,t}\right)} \end{aligned} \tag{14}$$

[4] That is, the approach is subject to the same "fishing license" critique made by Fama (1991) and Cochrane (2001). See also Chen (2003).

where $\frac{cov(e_{i,t},u_{1,t})}{var(u_{1,t})}$ is the market beta. What will happen if we omit the second state variable x? In this case the surprise in the market return will be $y_t = u_{1,t} + \alpha_2 x_{t-1}$, and the two new betas are

$$\beta_{i,DR,new} = -\frac{\rho\alpha_1}{1-\rho\alpha_1} \times \frac{cov\left(e_{i,t}, u_{1,t}\right)}{var\left(y_t\right)} - \frac{\rho\alpha_1}{1-\rho\alpha_1} \times \frac{cov\left(e_{i,t}, \alpha_2 x_{t-1}\right)}{var\left(y_t\right)} \tag{15}$$

$$\begin{aligned} \beta_{i,CF,new} &= \frac{cov\left(e_{i,t}, u_{1,t}\right)}{var\left(y_t\right)} + \frac{cov\left(e_{i,t}, \alpha_2 x_{t-1}\right)}{var\left(y_t\right)} - \beta_{i,DR,new} \\ &= \frac{1}{1-\rho\alpha_1} \times \frac{cov\left(e_{i,t}, u_{1,t}\right)}{var\left(y_t\right)} + \frac{1}{1-\rho\alpha_1} \times \frac{cov\left(e_{i,t}, \alpha_2 x_{t-1}\right)}{var\left(y_t\right)}. \end{aligned} \tag{16}$$

A comparison of the old and new betas suggests the following effects from omitting x: both the DR beta and the CF beta are changed, but in the opposite direction if $\alpha_1 > 0$, which is the case in Campbell and Vuolteenaho (2004A) because equity return has positive autocorrelation. To understand this, we note that the omitted state variable will show up in the residual of the excess market return. This will change both the DR beta and the market beta, but not in the same direction because of the negative sign in the DR beta. The CF beta, as the difference between the market beta and the DR beta, will be in the opposite direction from the DR beta. Therefore, if an omitted state variable (factor) covaries differently with different stocks, *ceteris paribus*, it can induce false cross-sectional patterns for CF betas and DR betas – in this example in the opposite directions.

In general, the DR beta is a single number that measures the combined effect of all factors. The inclusion/exclusion of different factors, if they have different cross-sectional effects on stocks, will induce different cross-sectional patterns in the DR betas. The CF betas are also affected because they are backed out from the DR betas.[5] Similarly, it can also be shown that omitting a state variable can induce biases in the relative variances of the DR news and CF news, although the direction of the bias varies depending on additional assumptions.

While model misspecification is always a potential problem for any estimation model, this problem is likely to be much more severe in the return decomposition approach. In a regular multifactor regression, the omission of some factors will increase noise, but we can still draw inference on the specified factors if the omitted factors are not correlated with the specified ones. In the decomposition approach, the omission of state variables will directly affect both the DR news and the CF news, and the relative balance between them. Therefore, when the CF news is derived as the residual component, any conclusion drawn from the comparison of the CF news and DR news, in terms of either the relative magnitude of the variances or the cross-sectional patterns of the betas,

[5] In the example we assume $\alpha_1 > 0$. If $\alpha_1 < 0$, there are still cross-sectional patterns, due to missing factors, of the DR and CF betas, though they might not run in the opposite directions. If $\alpha_1 = 0$, then the missing factors are likely to have little influence on the DR betas but mainly show up in the CF betas. The bottom line is that the cross-sectional biases due to the missing factors exist regardless of the sign of α_1.

could be unreliable because it is driven by the factors included.

Current literature This discussion has direct implication for the current literature. In the original studies of the return decomposition approach (Campbell and Shiller (1988A, 1988B), both the DR and CF news are directly modeled. In most of the subsequent works, the CF news is usually backed out as the residual component.[6] Among them, Campbell (1991), Campbell and Ammer (1993), and Vuolteenaho (2002) study the relative variances of the CF news and the DR news; Campbell and Mei (1993), Campbell and Vuolteenaho (2004A), Koubouros, Malliaropulos, and Panopoulou (2004), and Campbell, Polk, and Vuolteenaho (2005) estimate the CF betas; Hecht and Vuolteenaho (2006) use residual-based CF proxies to study whether the relation between equity return and CF proxies represents CF news; Campbell and Vuolteenaho (2004B) use residual-based CF proxies to study how inflation illusion explains asset misvaluation; in the macroeconomics literature, Patelis (1997) and Bernanke and Kuttner (2004) study how unexpected monetary policy changes can affect stock returns through DR news and CF news; in the accounting literature, Callen and Segal (2004) and Callen, Hope, and Segal (2005) model DR news and back out either accrual news or foreign earnings news as the residual components and study their importance.

This study only concerns the corresponding parts of these studies – they also explore many interesting questions that are outside of our concern.[7] Because these papers choose state variables based on their priors, although they usually provide extensive robustness checks on their estimations, they do not focus on the sensitivity with respect to state variables. Nevertheless, almost all studies recognize this limitation and acknowledge that the conclusions are based on the particular VAR systems (see Campbell and Ammer (1993) for detailed discussions). The question less addressed, however, is to what extent the conclusions are sensitive to model specifications. The answer to this question is important because, while the choices of state variables are particular to each study, the conclusions are usually general and have broad academic as well as practical implications.

We emphasize that the problems discussed here are all empirical. The return decomposition approach is intuitive and theoretically sound so long as the DR can be properly estimated through a VAR system. The issue we look into is what will happen given imperfect predictive power on the DR. In the rest of this paper we examine the sensitivity of three patterns – the relative variances

[6] The usual argument for avoiding the direct modeling of the dividend growth rate (the CF component) includes (i) that it enables the use of monthly data and (ii) that dividend growth rate might not be properly captured in a linear VAR system.

[7] For example, in both Campbell and Ammer (1993) and Campbell and Mei (1993) the real interest rate news is directly considered; in these papers the impact of each state variable is directly pursued. Because these state variables are directly modeled, the problems we discussed do not directly apply to them.

of the DR news and CF news, the magnitude of DR betas and CF betas, and the cross-sectional patterns of the betas – to different choices of state variables.

3 Treasury bond returns

We first apply the return decomposition approach to Treasury bond returns. For equity returns, the omission of certain state variables will yield an estimated CF news that consists of the true CF news plus the noise due to our limited ability to predict DR. For Treasury bonds, however, the nominal cash flows are fixed. Any real interest rate shock or inflation shock can only be incorporated into the discount rate, and affect bond returns through that channel. That is, unexpected Treasury bond returns can only reflect changes in future discount rate, not nominal bond cash flows. If we apply the return decomposition, the estimated "CF news" must be purely modeling noise. Therefore, Treasury bonds provide a unique opportunity to examine what happens if we have limited ability to predict DR.

We use a similar log-linear approximation as before:

$$e_{t+1} = (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{N} \rho^j \Delta d_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{N} \rho^j r_{t+1+j} \tag{17}$$

though we know by definition that the first term, the "CF news,"must be zero. In addition, in the equation above we have adjusted the maturity to N periods, which means the DR news is equal to

$$e_{DR,t+1} = e1' \lambda_1 u_{t+1}, \tag{18}$$

where $\lambda_1 = \left(\rho\Gamma - \rho^N \Gamma^N\right)(I - \rho\Gamma)^{-1}$. Campbell and Ammer (1993) show that, in the case of zero-coupon bonds, the following equation holds exactly (Equation A4 in their paper):

$$e_{t+1} - \left(- (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{N} r_{t+1+j} \right) = 0, \tag{19}$$

which says that the difference between unexpected bond return and DR news (i.e., CF news by definition) must be zero. It then follows that

$$e_{DR,t+1} = e1' \lambda_2 u_{t+1}, \tag{20}$$

where $\lambda_2 = \left(\Gamma - \Gamma^N\right)(I - \Gamma)^{-1}$.[8] In the rest of the study we will calculate the DR news using λ_1. Using the equation involving λ_2 makes little difference because ρ is a number very close to one. In any case we will calculate the CF news as the residual component.

[8] Campbell and Ammer (1993) point out that there will be some modeling noise because of the change of bond maturity from one period to the next. Because we use monthly data, this noise is likely to be very small and is not expected to be the main driver of the results.

We study three patterns: (i) the relative variances of the DR news and CF news, (ii) the magnitude of the betas, and (iii) the cross-sectional trends of the betas. We know the actual CF variance must be zero. Therefore, if the model is properly specified, the DR variance will far exceed the CF variance. In addition, the CF betas are expected to be close to zero and thus there should be no cross-sectional dispersion of the CF betas. Furthermore, bond portfolios with longer maturity are expected to have higher DR betas because of the discounting effect on more remote cash flows (see Campbell and Vuolteenaho (2004A) for a similar argument for equities with remote cash flows).

Results on Treasury bond returns are shown in Table 1. In Panel A, we use the Ibbotson dataset covering the 1926:01-2002:12 period at the monthly frequency. We use the intermediate-term bonds as the bond market portfolio.[9] We employ a VAR system with the excess return of the bond market portfolio as the first element. The state variables used to predict bond returns are chosen following the literature: the term spread, the expected real interest rate, the expected inflation, and the credit spread (Baa over Aaa yield).[10] The expected real interest rate and inflation are estimated following Fama and Gibbons (1982).[11]

The R-squared of the VAR regression for the bond return prediction equation is about 2.7%, which is very close to that of the equity return prediction equation in Campbell and Vuolteenaho (2004A) (2.57%). The purpose of this exercise is to examine the patterns given the limited explanatory power of the return prediction equation. The consistency of the R-squared in the bond and equity return prediction equations makes the comparison between them reasonable.

In Panel A the CF variance is much larger than the DR variance. This "CF news" is in fact the DR news that is not picked up by our VAR model specification. The fact that the CF variance, which is supposed to be zero, outweighs the DR variance suggests that model misspecification can play a crucial role in the relative magnitude of the two variances. Put differently, a conclusion based on the relative variances using this method might not be reliable.

In Panel B we calculate the CF betas and DR betas for three portfolios using the same bond market portfolio as in Panel A; these portfolios differ in their maturities. Two patterns emerge in this panel. First, the magnitude of the CF betas is always higher than that of the DR betas,

[9] Treasury bond returns are, by definition, driven by systematic macroeconomic factors. Therefore any of the bond portfolios can reflect the systematic risks and serve as a proxy for the bond market portfolio.

[10] This literature includes, among others, Shiller (1979), Shiller, Campbell, and Schoenholtz (1983), Fama (1984), Keim and Stambaugh (1986), Fama and Bliss (1987), Fama and French (1989), Campbell and Shiller (1991), Ferson and Harvey (1991, 1993), and Baker, Greenwood, and Wurgler (2003).

[11] We adopt this procedure to be consistent with some recent studies in predicting bond returns (Baker, Greenwood, and Wurgler (2002)). Alternatively, we can use nominal interest rate (instead of the expected real interest rate and inflation) as the state variable. The results are similar and are available upon request.

which is consistent with what we find regarding the relative variances. Second, bonds with longer maturity are expected to have higher DR betas but zero CF betas. In stark contrast, we find that the DR betas monotonically decrease with maturity, while the CF betas monotonically increase with maturity. The opposite directions of the DR betas and CF betas are consistent with our earlier theoretical example.

The patterns in Panel B are further confirmed in Panel C. In particular, Panel C1 uses the monthly return data of Fama-Bliss zero-coupon bonds covering the 1952:06-2003:12 period. We use the 6-month-maturity return as the bond market portfolio and calculate the betas for maturities ranging from one to five years. Panel C2 reports betas for the Fama bond portfolios, obtained from CRSP, covering the 1952:01-2003:12 period. The maturities range from one to ten years.

For the 15 portfolios in Panels C1 and C2, the patterns are monotonic: the magnitude of CF betas is much larger than the magnitude of DR betas; CF betas increase with maturity while DR betas decrease with maturity. The reported bootstrapped standard errors (with 2500 realizations) indicate that the differences of these betas are highly significant.

Therefore, the evidence seems to suggest that for the Treasury bond market the CF risk outweighs the DR risk, which is reflected in the magnitude of both the CF variances and betas; and that higher duration bonds have higher CF risk but lower DR risk. Of course, we know that all these patterns are false, because Treasury bonds have no nominal CF risk. These false patterns are all caused by our limited ability to forecast expected returns, which leads us to draw wrong conclusions.

To obtain the results above, we have used excess bond return, which is decomposed into the DR and CF news components. This procedure is different from that of Campbell and Ammer (1993) who use bond yield (instead of actual returns), decomposed into three DR news components. The procedure we use is proper for our purposes because it exactly matches what has been done to the equity returns in Campbell and Vuolteenaho (2004A): the realized excess returns are used, and the DR and CF news are separated. Using bond yields (instead of realized returns) will increase the predictive power, but the matter of interest is the patterns that emerge given *imperfect* predictive power on the DR. The consistent treatment on both equity and bond makes the comparison meaningful.

We have tried some alternative specifications: (i) replace the real interest rate and inflation with the nominal interest rate in the VAR system; and (ii) use bond returns instead of the excess bond returns. In all these specifications the CF news remains a significant component (compared

to the DR news) and there is always a systematic cross-sectional variation of the CF betas.[12]

The evidence from the Treasury bond market has direct implications on what we can infer from the equity market. The forecasting power, in terms of the R-squared, is very similar in both markets in our VAR regressions. There is no obvious reason to believe that the false patterns in the bond market do not show up in the equity market.

4 Equity returns

We turn now to the equity market. Unlike treasury bonds, equities have both CF risk and DR risk, and it is not easy to distinguish what portion of the estimated CF news is actual CF news and what portion is due to our limited ability to forecast expected returns. Nevertheless, consistent with the intuition from the bond market, we know that different information sets (for the prediction of the expected returns) could change the estimated CF news and DR news, and all subsequent conclusions based on the comparison between them. Therefore, here we alter the information set and examine (i) the relative variances of the DR news and CF news in the market portfolio, and (ii) the cross-sectional patterns of the two betas. In the latter part of the paper we also attempt to model both DR news and CF news directly in an effort to separate actual CF news from modeling noise.

4.1 Variances of the market portfolio

Campbell and Vuolteenaho (2004A) use four state variables in their VAR system: (i) excess equity market return; (ii) the term spread; (iii) the 10-year smoothed PE ratio; and (iv) the value spread. The first variable is necessary to decompose returns, while the others are optional. We call their combination of the state variables the *benchmark case* throughout the paper.

Table 2 reports the variances of DR news and CF news of the equity market portfolio and their covariances. Panel A is based on monthly data covering 1929-2001, which is the sample period Campbell and Vuolteenaho (2004A) studied and we use their own data whenever possible. In the first column, where the benchmark case is used, the CF variance is 0.27% and the DR variance is 0.06%. Therefore, consistent with Campbell and Ammer (1993), DR news far exceeds CF news in driving aggregate equity returns. In the second column, we drop the PE ratio from the benchmark case and find that the CF variance is 0.44% and the DR variance is 0.05% – the trend is completely reversed.

Why does the PE ratio make so much difference? As Campbell and Vuolteenaho (2004A) point

[12] The results are available upon request.

out, the importance of any state variable depends on the coefficient in VAR estimation and its persistence. In the benchmark case, the return prediction coefficients (the first row of Γ) are as follows

$$r_{M,t+1} = 0.094 \times r_{M,t} + 0.006 \times TY_t - 0.014 \times PE_t - 0.013 \times VS_t + u_{1t}. \tag{21}$$

where $r_{M,t}$ is the excess return, TY_t is the term spread, PE_t is the 10-year PE ratio, and VS_t is the value spread. The coefficient for the PE ratio (-0.014) is not particularly high. However, this 10-year smoothed PE ratio is highly persistent: regressing it on its own lag yields a coefficient of 0.994 and an R-squared of 99.1%. As a result, the first row of λ, which considers the infinite sum, is $[-0.398\ 0.011\ -0.883\ -0.284]$; the PE ratio becomes the dominant factor due to its persistence.

Now let's take a closer look at how PE ratio works. The CF news is equal to

$$e_{CF,t+1} = e1'u_{t+1} + e1'\lambda u_{t+1}, \tag{22}$$

where $e1'u_{t+1}$ is unexpected equity excess return and $e1'\lambda u_{t+1}$ captures how the shocks to the state variable vector, u_{t+1}, affect future equity returns. *By construction*, a shock to the PE ratio is highly correlated with contemporaneous equity return; in the meantime, it predicts one period-ahead return with a small negative coefficient (-0.014), which is transformed into a large coefficient of -0.883 due to persistence. Clearly, ceteris paribus, the more persistent the PE ratio, the smaller the CF news. Given the little predictive power of the return equation (R-squared of 2.6%), very persistent state variables are needed to make the DR news larger than the CF news.

Of course, at least part of the persistence of the 10-year smoothed PE ratio is by construction. This begs the question of what will happen if we replace this PE ratio by similar variables that also work as proxies for expected returns. In the third column of Panel A, we use 1-year smoothed PE ratio and find the CF variance at 0.09% and the DR variance at 0.16%; the two variances are much closer than the benchmark case. In the fourth column we use the dividend yield, which is more commonly used to predict equity returns (e.g., Campbell and Shiller (1988A), Campbell and Mei (1993), Campbell and Ammer (1993), and Campbell and Vuolteenaho (2004b)), and find the CF variance at 0.14% and the DR variance at 0.12%.

In the sixth column we use the book-to-market spread, defined as the book-to-market of value stocks minus that of growth stocks. We use this variable because Liu and Zhang (2006) show that the value spread is less effective to pick up the counter-cyclicality of expected return. We find that the inclusion of this variable makes the 10-year PE ratio insignificant, which is subsequently dropped, while increases the statistical significance of every other variable. That is, the use of this variable (rather than the 10-year PE ratio) improves the predictive power of the VAR and is an

intuitive proxy for expected return. Nevertheless, this specification leads to a CF variance at 0.36% and a DR variance at 0.10%. We further add the corporate issue activity, defined as the 12-month moving sum of net issues by NYSE stocks divided by total market capitalization of NYSE stocks (Baker and Wurgler (2000)), to this specification in Column 7 because this combination gives the best predictive power at monthly frequency (R-squared at 3.5%). We find that the CF variance is still much higher. Finally, replacing the book-to-market by the 1-year PE ratio, together with some other variables, as shown in the last column, will make the DR news more important.

Panel B reports the results for 1952-2001 (post Treasury-Fed Accord) to provide a better comparison with Campbell and Ammer (1993). Similar to Panel A, we see the flip of importance of the CF variance and DR variance depending on the VAR specification. For example, the use of 1-year PE ratio makes the CF variance slight larger than the DR variance. Simply put, the relative importance of CF variance and DR variance is sensitive to minor alternation of state variables. Panels C and D report the results using annual data and point to a similar flipping pattern. We can use more state variables to illustrate this flipping pattern; we only report the specifications in Table 2 because they show clearly how the approach works and its sensitivity.

The relative magnitude of CF variance and DR variance is important because of its modelling implications.[13] A related empirical literature, directly or indirectly, debates about this relative importance (e.g., Roll (1988), Fama (1990), Stambaugh (1990), Kothari and Shanken (1992), Campbell and Ammer (1993), Cochrane (1992, 2006), Ang (2002), and Lettau and Ludvigson (2005)). Given the flip we observe in Table 2, we are hesitant to draw any conclusion on this issue. Rather, the case in point is that the evidence provided through the variance decomposition approach might be sensitive to the state variables included.[14]

4.2 Cross-sectional patterns

4.2.1 The benchmark case

Campbell and Vuolteenaho (2004A) decompose the value-weighted equity market return, covering the 1929:01-2001:12 period, into the CF news and DR news. They then calculate the CF betas and DR betas for the 25 Fama-French portfolios sorted by size and market-to-book ratio. They also create 20 more portfolios sorted by the loadings on the state variables. They find that, while the CAPM betas largely fail to explain the cross-section of equity returns for the post-1963 period, the

[13] See, for example, the macroeconomics literature. To explain the equity premium puzzle, Campbell and Cochrane (1999) focus on modeling the DR risk while Bansal and Yaron (2004) model both DR risk and CF risk.

[14] We have also tried to include dividend growth rate into the VAR, and thus directly model both the CF news and DR news. In that case we find that the CF variance appears to be smaller than the DR variance in many occasions, but there are again flips depending on the state variables.

CF betas and DR betas do so very successfully.

Table 3 is a brief replication of what is achieved in Campbell and Vuolteenaho (2004A). In Panel A we report the CAPM betas, CF betas, and DR betas. For the pre-1963 period, the CAPM beta decreases with size and increases from growth to value firms, consistent with the return patterns related to these firm characteristics. Accordingly, the CAPM beta can explain about 40% of the cross-section of equity returns. For the post-1963 period, the CAPM beta still decreases with size, but it also declines from growth to value firms. Because the two patterns largely cancel each other out with respect to returns, the CAPM beta is insignificant in the cross-section of returns (see also Ang and Chen (2005) and Fama and French (2005)).

The CF betas and DR betas we calculate are very close to those in Campbell and Vuolteenaho (2004A).[15] For the period before 1963, both betas decrease with size but increase from growth to value stocks. Combined, they can explain 45% of the cross-sectional return variation. In the period after 1963, the CF beta is relatively flat with size, while the DR beta decreases with size. On the other hand, the CF beta increases (and DR beta decreases) from growth to value stocks, but the trend is relatively stronger for the CF betas: they usually more than double from growth to value stocks. Therefore, in the cross-sectional regression, the CF betas will pick up the variation of returns from growth to value firms and the DR betas will pick up the variation from small to larger firms. Combined, they explain 50% of the variation, compared to the meager 2% by the CAPM. Based on the evidence, Campbell and Vuolteenaho (2004A) conclude that it is CF beta, not DR beta, that matters. The DR betas would have suggested that value firms earn lower returns, contrary to the actual return pattern.

4.2.2 Replacing the benchmark case with similar variables

While Table 2 highlights the importance of a persistent 10-year PE ratio in driving the time series results in the decomposition approach, Table 4 explores the same results for the cross-section. The standard errors reported in the table are obtained through bootstrapping with 2500 realizations. We focus on the post-1963 period because the CAPM breaks down in this period.

In Panel A we exclude the PE ratio from the benchmark case. The CF beta significantly declines from growth to value firms. For example, the CF beta for small growth stocks is 1.74, which shrinks to 1.44 for small value stocks. The difference of -0.30 is highly significant with a standard deviation of 0.07. The same trend holds for all other portfolios. In addition, the magnitude of the CF betas

[15] Our decomposed CF news and DR news are identical to those in Campbell and Vuolteenaho (2004) (available on Vuolteenaho's website) up to the third decimal point. Because of the small variance of the excess return residual, our betas, defined as the covariance terms divided by the variance, are slightly different from those in Campbell and Vuolteenaho (2004) at the second decimal point. Nevertheless the trends and conclusions are identical.

is much larger than that of the DR betas, consistent with the results in Table 2 that, once the PE ratio is excluded, CF variance appears to be more important.

In general, in order for value stocks to have higher CF betas, we find that both the 10-year PE ratio and the value spread must be included. Considering all the possible combinations of the variables in the benchmark case, in more than two-third of these combinations value stocks have lower CF betas.

Two patterns are noteworthy in the cross-sectional regression in Panel A2. First, the CF beta has a significantly positive coefficient, but it does not mean that value stocks earn higher returns because they have higher CF betas; in fact Panel A1 shows that they have lower CF betas. The coefficient is positive presumably because smaller stocks have higher CF betas. In other words, this positive coefficient is related more to the cross-sectional difference in size than to market-to-book ratio. Second, the R-squared is 52%, which is higher than that in the benchmark case. Therefore, the exclusion of the PE ratio does not lead to a drop in the cross-sectional explanatory power.

In Panels B1-B4 we study various cases where the 10-year PE ratio is replaced by similar proxies for the expected return, including: (i) 1-year PE ratio; (ii) dividend yield; (iii) the Dow Jones book-to-market ratio (e.g., Kothari and Shanken (1997), Pontiff and Schall (1998), and Lewellen (1999)); and (iv) the book-to-market spread plus the corporate issue activity. The rationale for using most of these specifications has been explained previously. For brevity we only report the cross-section pattern of CF betas, although in all cases the DR beta declines from value to growth stocks. In all sub-panels we observe a declining trend of the CF beta from growth to value stocks. Therefore, similar to Table 2, the cross-sectional pattern is sensitive to minor specification alternations, but the pattern is more stable in this case as they all point to a declining trend of CF beta from value to growth stocks.

Finally, the 10-year smoothed PE ratio in the benchmark case is from Shiller (2000), which has been updated by Shiller. We thus replace the old PE ratio with the updated one for the same time period covering the benchmark case.[16] The result, shown in Panel B5, indicates that the trend of the CF beta from growth stocks to value stocks is again reversed from the benchmark case. This finding is surprising because the two PE ratios are supposed to be the same. As can be seen in Figure 1, the two time series are not identical but nevertheless track each other very closely, with a correlation of 92%. How could two similarly persistent PE ratios (both with autocorrelation at 99%) yield opposite beta patterns? When the benchmark variables are used, the

[16] We thank Robert Shiller for making the data available through his website. We also confirmed with him the accuracy of the data.

estimated return prediction equation (suppressing the intercept term) is reported in Equation (21). The corresponding coefficients that consider how current innovations affect equity return, $e1'\lambda$, are $[-0.398\ 0.011\ -0.883\ -0.284]$. When we use the PE ratio from Shiller, the prediction equation is

$$r_{M,t+1} = 0.095 \times r_{M,t+1} + 0.006 \times TY_t - 0.011 \times PE_t - 0.008 \times VS_t + u_{1t}. \tag{23}$$

Only the coefficient on the value spread is "largely" affected (from -0.013 in Equation (21) to -0.008). However, the corresponding $e1'\lambda$, is $[-0.372\ 0.015\ -0.841\ -0.077]$. It is clear that the importance of the value spread variable has been largely changed relative to other variables, leading to cross-sectional betas drastically different from the benchmark case. We also find that with the updated benchmark case the R-squared has dropped sharply from 50% to 12%. In other words, even in the benchmark case, once we use the updated PE ratio, the trend of CF betas is reversed, and the explanatory power of the cross-sectional regression largely disappears.

Therefore, Tables 2 and 4 suggest that the benchmark case relies critically on a highly persistent 10-year smoothed PE ratio. This dependence is problematic because its persistence is at least partly by construction and we find that it easily fails most stationarity tests. However, once this variable is replaced by similar but usually less persistent variables, then the time series results become unstable, and the cross-sectional pattern reverses. But this does not mean that a more persistent PE ratio is always more "helpful". The updated PE ratio is similarly persistent, but its minor impact on other state variables can also reverse the beta pattern.

4.2.3 Other state variables

The state variables in the first-stage VAR regression are meant to help predicting equity returns. Given the large set of known variables that can predict equity returns, there is no obvious reason why we have to restrict to the variables in the benchmark case. In this subsection we examine whether the results for CF betas are sensitive to some of these alternative variables. While we experiment with many, we only present two cases that are representative and easy to interpret.

Panel A of Table 5 includes the set of variables from Petkova (2006) that have clear macroeconomic meaning and can absorb the Fama-French risk factors: the excess market return, the term spread, the dividend yield, the credit spread (Baa over Aaa yield), and the riskfree rate. In this case, the CF beta decreases significantly from growth to value stocks.

Panel B presents the case in which we can largely increase the predictive power on equity return in the first-stage VAR regression. It adds three state variables – *cay* from Lettau and Ludvigson (2001A, 2001B) and the risk-premium factor and the volatility factor from Ludvigson and Ng (2005) – to the benchmark case. These state variables increase the R-squared of the equity return

prediction from 2.57% in Campbell and Vuolteenaho (2004A) to 14%. Panel B indicates that the inclusion of these variables wipes out the cross-sectional patterns of the CF betas in the benchmark case.

While not reported, we also experiment with the long list of state variables from Goyal and Welch (2005) that seem to be the most recent comprehensive set of variables with somewhat predictive power on equity returns. It is fair to say that for most of the combinations, value stocks do not have higher CF betas. The reason, we believe, is simple: the evidence that value stocks have lower CAPM betas for the post-1963 period is robust. So long as portfolio equity returns are used (as in Campbell and Vuolteenaho (2004A)), it takes a special specification to reverse the trend. Campbell and Vuolteenaho (2004A) happen to have a prior that relies critically on a highly persistent PE ratio and the value spread. While their results are to some degree robust so long as these two particular variables are used, they are sensitive to minor alternations to these variables.

4.2.4 Direct modeling of the CF news

One question arises naturally. Given the drawback of the residual-based return decomposition approach, what will happen if we model both CF and DR news directly? Here we directly model CF news in VAR. Such a procedure amounts to breaking the CF news in the current decomposition approach into the direct CF news and a model noise. We explore this approach using two different cash flow proxies: dividend growth rate and earning on book equity (also called ROE, return on equity).

Dividend growth rate With dividend growth directly included in the VAR, we can revise our earlier log-linear approximation as follows:

$$e_{t+1} = e_{CF,t+1} - e_{DR,t+1} + residual, \tag{24}$$

where $e_{DR,t+1}$ is the same as before. The residual variable represents the component of the unexpected return that is not captured by our modeled CF news and DR news. We adopt a separate VAR system for the dividend growth rate because the state variables that predict equity return do not necessarily predict dividend growth rate.[17] If we place the dividend growth rate of the market portfolio as the first component in the growth rate VAR, it can be easily shown that

$$e_{CF,t+1} = e1'\lambda_3\varpi_{t+1}, \tag{25}$$

[17] Alternatively, this can be regarded as a single VAR system with equity return and dividend growth rate included, and with parameter restrictions.

where $\lambda_3 = (I - \rho\Gamma)^{-1}$, Γ is the companion matrix, and ϖ_{t+1} is the residual vector. In addition, we further decompose the CF news into $e1'\varpi_{t+1}$, which we call the current CF news, and $e_{CF,t+1} - e1'\varpi_{t+1}$, which we call the future CF news. Intuitively, the current CF news picks up the current innovations in the dividend growth rate and the future CF news picks up the impact of current innovations on future dividend growth. We separate the two terms because the current CF news relies less on the specification of the VAR system while the future CF news depends critically on λ_3, and thus on the estimated coefficients of the VAR system. Finally, we construct the residual component after the CF news and DR news are both considered.

In Panel A of Table 6 we report the betas for the 25 portfolios. The state variables in the DR VAR system are the same as those in the benchmark case. The state variables in the dividend growth rate VAR include dividend growth rate (of the market portfolio), market equity return, and dividend yield. These variables are included because of their ability to forecast dividend growth.

As is clear in the panel, value stocks have lower current CF betas and future CF betas, and thus lower total CF betas; they also have lower DR betas as found before. However, value stocks have higher residual betas. When the CF betas and the residual betas are combined, which is equivalent to modeling the DR news but backing out the CF news as the residual, the combined betas are higher for value stocks. The cross-sectional pattern of the CF betas is opposite to the benchmark case, while the pattern of the combined (CF+residual) betas is identical to the benchmark case. This evidence indicates that the higher CF betas for value stocks in the benchmark case are driven by the residual news. When dividend growth rate is directly modeled, growth firms have higher CF betas and DR betas. The value premium puzzle remains.[18]

Of course, the residual news could represent CF news that is not captured in our model. A wide range of conclusions can be drawn depending on how much of the residual news is related to CF news. For example, in the benchmark case, the increasing trend of the CF beta from the growth stocks to the value stocks becomes clear only if we assume that more than 80% of the residual news is in fact unmodeled CF news. Otherwise we have to conclude that either there is no trend, or there is a decreasing trend. This exercise suggests the difficulty of drawing meaningful conclusions using the residual-based return decomposition approach.

We experiment with other state variable specifications in the dividend growth VAR, including adding cdy – Lettau and Ludvigson (2005) show that the variable predicts dividend growth. We find that our conclusion does not change.

[18] It is also interesting to look at the DR beta plus the noise beta, which is equivalent to modeling the CF news but backing out the DR news as the residual. In this case the original strong declining trend of the DR beta from growth to value stocks is not clear anymore.

Return on equity One critique of using the dividend growth rate as the cash flow measure is that it is subject to corporate policies and might be difficult to predict (e.g., Ang and Bekaert (2005)). There is another way to decompose returns and avoid using dividend-related measures. In particular, let's pair the definition of equity return and return of equity (ROE):

$$r_t = \ln\left(\frac{M_t + D_{t+1}}{M_{t-1}}\right) \tag{26}$$

$$ROE_t = \ln\left(\frac{B_t + D_{t+1}}{B_{t-1}}\right), \tag{27}$$

where M_t and B_t are the market and book size of the firm respectively. Applying log linearization to the right hand side of both equations, subtracting the two equations, and iterating forward, one can obtain the following in the limit (see Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003)):

$$b_t - m_t = \text{constant} + \sum_{j=1}^{\infty} \rho^{j-1} \left(r_{t+j-1} - e_{t+j-1}\right), \tag{28}$$

where $b_t - m_t$ is the log book-to-market. It further suggests that

$$e_{t+1} = (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{N} \rho^j ROE_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{N} \rho^j r_{t+1+j}, \tag{29}$$

where e_{t+1} is the unexpected equity returns as before. This equation is symmetric to Equation (1) except that we have replaced dividend growth rate by ROE. Just like the dividend growth rate case, we assume that equity return can be predicted using a VAR involving the same state variables as in the benchmark case. In addition, ROE can be estimated using a VAR including ROE, excess equity return, and book-to-market. We use the merged CRSP-COMPUSTAT dataset to create a market portfolio and calculate the ROE and book-to-market of the market portfolio. When the book equity is not available in COMPUSTAT, we resort to Moody's book equity as used in Davis, Fama, and French (2000). The final data with market ROE and book-to-market is at the annual frequency covering the 1930-2001 period. We then apply the return decomposition and report the results in Panel B of table 6.

Using ROE as the alternative cash flow measure yields the same inference as those using the dividend growth rate. In particular, value firms have lower total CF betas, lower DR betas, but higher residual betas. When the residual betas are combined with the total CF betas, which is equivalent to modeling CF news as the residual, we obtain the same results in Campbell and Vuolteenaho (2004A), i.e., value stock have higher combined CF betas. Again, the results in the benchmark case are driven by the residual betas.

4.2.5 Further robustness checks

Industry portfolios If the CF beta is important for the purpose of calculating the cost of equity, it should be priced in most portfolios. Thus far our tests center on 45 portfolios, most of which are sorted by size and market-to-book ratio. Such a procedure is, to some extent, subject to the criticism that the patterns might be driven by firm characteristics instead of systematic risks (Daniel and Titman (1997, 2006)). One way to test the robustness of the CF beta is to investigate whether it is priced in the 48 industry portfolios defined by Fama and French (1997).

We use the same state variables as in the benchmark case and the results are reported in Table 7. We first calculate the CF betas and DR betas for each industry. To facilitate interpretation, we sort these industries into 16 cells by a two-way independent sorting of CF beta and DR beta. We then report the average returns of each cell in Panel A. While the patterns are not smooth, it is clear that industries with lower CF betas tend to have higher equity returns.

This observation is confirmed in Panel B, where we run a cross-sectional regression of the average excess returns on the two betas. The CF beta is priced in the wrong way: The regression coefficient is significantly negative, suggesting that portfolios with higher CF betas should earn lower expected returns and should be assigned lower costs of capital, contrary to the risk interpretation of CF betas.

Post-1952 data When implementing the return decomposition approach, Campbell and Vuolteenaho (2004A) first decompose the excess market return for the full 1929:1-2001:12 period into the DR news and CF news; they subsequently calculate portfolios betas for the pre- and post-1963 periods separately. We have followed their procedure thus far. One interesting question is what will happen if we estimate the DR news and CF news using only the postwar data. This question is worth pursuing because Campbell (1991) documents a shift in variance from CF news to DR news after 1952 and CAPM breaks down only in the postwar period. As shown in Table 8, it turns out that this alternative procedure leads to dramatically different results – there is a clear decreasing trend of the CF beta from the growth stocks to the value stocks. That is, even if we use the same variables as in the benchmark case, the beta trend is reversed once we focus on the post-1952 data. In addition, this reversed trend appears to be stable when other state variables are used.

Magnitude of ρ, data frequency, and conditional beta For brevity we discuss the following results without reporting. As in Campbell and Vuolteenaho (2004A), we provide further robustness checks in the following dimensions: (i) the magnitude of ρ, (ii) the data frequency; and (iii) conditional betas. We find that changing ρ does not change the results. We have results (Panel B of

Table 5 and Table 6) indicating that using quarterly or annual data does not alter the conclusions. In addition, we adopt a 36-month rolling-window to estimate the conditional CF betas and DR betas for each portfolio. We find the same conclusions.

5 Reconciliation with the current literature and a final test

5.1 Reconciliation

A growing literature, which we call the cash flow literature, shows that value stocks have higher cash flow covariances with aggregate cash flow of the market (e.g., consumption) than growth stocks do. Two representative studies are Bansal, Dittmar, and Lunblad (2005) and Hansen, Heaton, and Li (2005). Campbell and Vuolteenaho's (2004A) good beta/bad beta model is derived from a consumption CAPM in Campbell (1993). Because both group of studies involve consumption growth, we first revisit the intuition in Campbell (1993), and then discuss its link to the cash flow literature.

Campbell (1993) intends to test the consumption CAPM without resorting to consumption data. To see the intuition, first write out the dynamic budget constraint:

$$W_{t+1} = R_{m,t+1}\left(W_t - C_t\right), \tag{30}$$

which says that next period wealth W_{t+1} is equal to this period wealth W_t (net of consumption C_t) multiplied by gross investment return $R_{m,t+1}$. Applying log linearization to this budget constraint and taking expectations, Campbell obtains

$$c_{t+1} - E_t c_{t+1} = \left(r_{m,t+1} - E_t\left[r_{m,t+1}\right]\right) + \left(E_{t+1} - E_t\right)\sum_{j=1}^{\infty}\rho^j r_{m,t+1+j} - \left(E_{t+1} - E_t\right)\sum_{j=1}^{\infty}\rho^j \triangle c_{t+1+j}, \tag{31}$$

which says that a positive surprise of log consumption must be related to a positive market wealth return, a positive return on future wealth, or a negative revision on future consumption growth. Therefore, the equation suggests that consumption news contains return news.

Using a Epstein-Zin (1989) type non-expected-utility model that can separate relative risk aversion (γ) from the elasticity of intertemporal substitution (σ), Campbell shows that expected risk premium of stock i, adjusted for a Jensen's inequality effect, is equal to

$$E_t\left[r_{i,t+1}\right] - r_{f,t+1} = \frac{1-\gamma}{\sigma-1}COV\left(r_{i,t+1}, \triangle c_{t+1}\right) + \frac{\gamma - \frac{1}{\sigma}}{1-\frac{1}{\sigma}}COV\left(r_{i,t+1}, r_{m,t+1}\right). \tag{32}$$

That is, expected risk premium is driven by equity return's covariance with consumption growth ($\triangle c_{t+1}$) and with market equity return ($r_{m,t+1}$). When $\gamma = \frac{1}{\sigma}$ (e.g., time separable power utility),

we obtain the standard result in canonical consumption CAPM where the right hand side shrinks to $\gamma COV\left(r_{i,t+1}, \triangle c_{t+1}\right)$.

Campbell (1993) substitutes out $COV\left(r_{i,t+1}, \triangle c_{t+1}\right)$ such that no consumption data is used. To achieve this, note that, assuming that asset return and consumption are jointly conditionally homoscedastic and lognormal, the Euler equation implies that

$$E_t\left[\triangle c_{t+1}\right] = \text{constant} + \sigma E_t\left[r_{m,t+1}\right], \tag{33}$$

which says that there is a linear relation between expected consumption growth and expected return on the market portfolio. This relation further suggests that the budget constraint equation (31) can be rewritten as

$$c_{t+1} - E_t c_{t+1} = \left(r_{m,t+1} - E_t\left[r_{m,t+1}\right]\right) + (1-\sigma) \times e_{DR,t+1}. \tag{34}$$

That is, consumption news can be written as a linear combination of unexpected market return and DR news. Substituting this into the expected return equation and we obtain

$$\begin{aligned} E_t\left[r_{i,t+1}\right] - r_{f,t+1} &= \gamma COV\left(r_{i,t+1}, r_{m,t+1}\right) + (1-\gamma) COV\left(r_{i,t+1}, e_{DR,t+1}\right) & (35) \\ &= \gamma COV\left(r_{i,t+1}, e_{CF,t+1}\right) + COV\left(r_{i,t+1}, e_{DR,t+1}\right). & (36) \end{aligned}$$

In the end, consumption growth has been substituted out and the expected risk premium is only a function of CAPM beta, DR beta, and CF beta.

We can learn the following from the above exercise. First, this way of substituting consumption out is elegant and intuitive. For $\gamma > 1$, and given that value stocks have lower $COV\left(r_{i,t+1}, r_{m,t+1}\right)$, Campbell and Vuolteenaho (2004A) aim to show that $(1-\gamma) COV\left(r_{i,t+1}, e_{DR,t+1}\right)$ will reverse this trend. However, as we have shown throughout the paper, such an exercise is sensitive to how DR news is modeled, and is not successful in most specifications.

Second, Campbell and Vuolteenaho (2004A) decompose the DR news and CF news of the *market* portfolio. They do not decompose those of individual portfolios for a simple reason. As shown from the expected premium equation (36) above, an individual portfolio's covariance between its return and market CF news – no matter whether the return represents CF news or DR news at portfolio level – will be assigned a higher price of risk than the covariance with market DR news does. Following model prediction, there is thus little reason to decompose the returns of individual portfolios.

In contrast, many studies in the cash flow literature, including Basal, Dittmar, and Lunblad (2005), Hansen, Heaton, Li (2005), and Da (2006), focus on the covariance between the cash flows

of *individual* portfolios and consumption growth. In some sense such an exercise is opposite to what Campbell and Vuolteenaho (2004A) do. This is because these studies are interested in cash flows of individual portfolios rather than of the market portfolio; and because they use consumption growth, which as shown in equation (34) contains both CF news and DR news of the market portfolio, while Campbell and Vuolteenaho (2004A) are interested in the relative importance of DR news and CF news of the market portfolio. The "CF news" of the two literatures thus has different meanings[19]; it is thus not necessarily surprising to see that value stocks do not have higher CF betas using the return decomposition approach but higher CF covariance with market consumption growth (see also Cohen, Polk, and Vuolteenaho (2003)).

A related literature shows that a careful calculation of the covariance between individual portfolio returns and consumption has the potential to explain the value premium; this literature includes, among others, Lettau and Ludvigson (2001B), Parker and Julliard (2005), Jgannathan and Wang (2005), and Yogo (2006). This literature differs from the cash flow literature in that it studies individual portfolio returns; it differs from Campbell and Vuolteenaho (2004A) in that it still uses consumption data, which contains both DR news and CF news of the market.

5.2 Further thoughts and a final test

Unlike other literatures, the return decomposition approach centers on the relative importance of CF news and DR news of the market portfolio, and thus the two components of CAPM beta. It has the drawback that, since the CF news is residual-based, the results are sensitive to how the DR news is modeled. On the other hand, compared to studies using direct CF measures, the residual-based CF news has the advantage that it can capture the CF news that is not embedded in current CF. Unsure whether the advantage outweighs the disadvantage, we do not know whether the "CF news" is indeed CF news or a catchall for noise.

There is a final test, however, that might shed light on the relative importance of CF news and DR news. By definition unexpected equity returns is either DR news or CF news (or both). Because a higher equity return, if it represents DR news, must imply a lower return in the future, the cumulative impact of DR news must be washed out in the long run. This intuition can be seen by rewriting Equation (1):

$$(\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j} = (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}, \tag{37}$$

[19] See theoretical models that emphasize on the importance of CF covariance with market consumption growth to explain the value premium, including, among others, Lettau and Wachter (2005), Santos and Veronesi (2005), and Kiku (2006).

which says that the return shock, with its impact on all future discount rates considered, must be all CF news because the temporal variation of DR offsets each other in the long run; in the limit, the cumulative equity return must be all about cash flow news (see also Hansen, Heaton, and Li (2005) and Bansal, Dittmar, and Kiku (2005)). Such a relation applies to both individual portfolios and to market portfolio. Similarly, the dynamic budget constraint equation (31) implies that

$$(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{m,t+1+j} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \triangle c_{t+1+j} \tag{38}$$

which says the shock on market return, with its impact on all future discount rates considered, must be all consumption news.

Because these two equations are essentially accounting identities, they should satisfy any asset pricing model. They thus suggest the following test: if we calculate CAPM beta using cumulative returns and consumption-CAPM beta using cumulative consumption growth, these betas should converge to CF-related betas as time horizon increases. Such a test relies little on how DR news or CF news is modeled; it considers both current information and updates on future expectations. In addition, it is related to the cash flow literature. For example, Basal, Dittmar, and Lunblad (2005) focus on CF news but is silent on DR news. Hansen, Heaton, and Li (2005) focus on long-run risk-return tradeoff, which is all about CF risk, but they do not show empirically how the DR variation in the short-run is washed out. Therefore, such a test can shed light on how the financial market values securities regarding DR risk and CF risk.

Table 9 reports results from such a test. In Panel A we report the cumulative CAPM betas from 1-year to 15-year horizons. The rationale is that the DR news in both individual portfolios and the market portfolio should be washed out in long horizons, and thus the long-term CAPM betas should reflect CF betas. Panel A shows, unfortunately, that value stocks have significantly lower CAPM betas for up to 15 years; there is no sign this trend is weakened or reversed in the long run. We report in Panel B the cumulative consumption betas from 1-year to 15-year horizons. The cross-sectional patterns are messy and do not support the hypothesis that value stocks have higher long-term consumption betas.[20]

In conclusion, it does not seem the case that the lower CAPM betas of value stocks are DR related, as argued by Campbell and Vuolteenaho (2004A). Alternatively, if we accept the prior that value stocks have higher CF covariance with market cash flows that should matter in the long run, then we do not understand, in the context of CF risk and DR risk, the mechanism in the financial market (i.e., returns) that links short-run and long-rum risks.

[20] The results on consumption betas are consistent with Parker and Julliard (2005) because they also suggest that the cross-sectional patterns do not converge in the long run.

6 Conclusions

The seminal work by Campbell and Shiller (1988A) provides a method where unexpected equity returns can be decomposed into cash flow (CF) news and discount rate (DR) news. In many subsequent studies that use this method, only the discount rate news is directly modeled, while the cash flow news is derived as the residual component. Some important conclusions have been drawn using this approach, including (i) that the variance of the DR news is larger than that of the CF news for the market portfolio and the DR betas are usually higher than the CF betas for portfolios, consistent with the claim that the time-variation of the equity risk premium plays a central role in driving aggregate returns; (ii) that value stocks earn higher returns because they have higher cash flow betas; and (iii) that, for the purpose of calculating the cost of equity, the more important measure of risk is the cash flow beta, not the total beta.

We argue that this approach should be followed with caution because the so called CF news, as the residual, might reflect model noise instead of actual CF news. Any misspecification in modeling the DR will affect the relative magnitude of the CF news and the DR news, and subsequently any conclusion drawn based on their comparison.

To illustrate this point, we decompose the returns of Treasury bonds, which are supposed to have zero nominal CF risk and no cross-sectional dispersion of CF betas. In contrast, we find that the variance of the "CF news" is usually larger than the variance of the DR news. In addition, bonds with longer maturities, which are supposed to have higher DR betas but zero CF betas, have lower DR betas but higher CF betas.

We then examine equity returns. We first show that the relative importance of CF variance and DR variance of the market portfolio is sensitive to minor changes to the state variables that predict returns. We then show that for most combinations of state variables that are known to predict stock returns, value stocks do not have higher CF betas. These results run counter to those reported in the current literature using the same approach. We further directly model the CF news, which amounts to dividing the CF news in the current decomposition approach into a direct CF news and a residual news. We find that value firms have both lower cash flow betas and discount rate betas, but higher residual betas, indicating that the results in the current literature are driven by the residual news.

We further reconcile our finding that value stocks do not have higher CF betas using the return decomposition approach with the finding in a related cash flow literature that value stocks have higher CF covariation with market CF. We conclude the paper with a test that suggests an

interesting unresolved issue on research on DR risk and CF risk.

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Table 1: Variance and beta decomposition of Treasury bond excess returns

We apply the return decomposition approach to Treasury bond returns. Panels A and B use monthly bond return data from Ibbotson covering the 1926:01-2002:12 period. In Panel A we decompose the excess return of intermediate maturity bonds into discount rate news and cash flow news, where the latter is calculated as the residual component following Campbell and Vuolteenaho (2004A). We then report the variances of the two components and their covariances. The state variables include different combinations of the term spread (the difference between the long-term and short-term bond yields), expected real interest rate, expected inflation, and credit spread (Baa over Aaa bond yield), where expected real interest rate and expected inflation are estimated following Fama and Gibbons (1982). The plus signs in Panel A indicate the selected variables in each scenario. In Panel B we use the intermediate-term bonds (from Panel A) as our bond market portfolio and calculate the discount rate beta and cash flow beta for three portfolios: inflation-adjusted 30-year T-bill return, inflation-adjusted intermediate-term bond return, and inflation-adjusted long-term bond return. Panel C1 uses the Fama-Bliss zero coupon bond return data for the 1952:06-2003:12 period. We use the 6-month zero-coupon bond as the bond market portfolio and then calculate the discount rate betas and cash flow betas for zero-coupon bond portfolios ranging from 1- to 5-year maturities. Panel C2 uses the Fama bond portfolios covering the 1952:01-2003:12 period. Again we use the 6-month bond return as the market portfolio and calculate the betas for portfolios with maturity ranging from 12 to 120 months. In Panel C the "diff" columns report the differences of betas of two adjacent portfolios. In Panels B and C we report bootstrap standard errors from 2500 simulated realizations.

Panel A: Variance decomposition

Variables in VAR				Variances		
Term Spread	Real Rate	Inflation	Credit Spread	Var(CF)	Var(DR)	Cov(CF, DR)
	+			1.9421	0.0771	0.2230
+				2.3140	0.1295	0.4352
+	+			2.3341	0.1425	0.4532
	+	+		1.9421	0.0771	0.2230
+	+	+		1.9953	0.1880	0.3078
	+	+	+	2.5403	0.6737	0.8247
+	+	+	+	2.5413	0.6755	0.8266

Panel B: Beta decomposition using Ibbotson data

	Full sample		1926:01-1963:5		1963:6-2002:12	
Inflation-adjusted portfolios	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}
30-day T-Bill (1)	0.0722	-0.0149	0.2341	-0.1692	0.0445	0.0087
Intermediate-term bonds (2)	1.3474	-0.1372	1.4048	-0.3046	1.3379	-0.1117
Long-term bonds (3)	2.0272	-0.1831	1.8762	-0.3092	2.0528	-0.1645
(3) - (1)	1.9550	-0.1682	1.6421	-0.1401	2.0083	-0.1732
Standard deviation of (3) - (1)	(0.1421)	(0.0993)	(0.2120)	(0.1535)	(0.1580)	(0.1409)

Table 1: Continued

Panel C						
Panel C1: Fama-Bliss zero coupon bonds						
Maturity	β_{CF}	Diff.	S.E. of diff	β_{DR}	Diff.	S.E. of diff
1-year	2.4417	-	-	-1.9587	-	-
2-year	3.1045	0.6628	(0.1185)	-2.5565	-0.5978	(0.1458)
3-year	3.4969	0.3924	(0.1151)	-2.9160	-0.3596	(0.1449)
4-year	3.8654	0.3685	(0.1709)	-3.2548	-0.3388	(0.2163)
5-year	4.2404	0.3750	(0.1511)	-3.5970	-0.3422	(0.1635)
Panel C2: Fama bond portfolios						
Maturity	β_{CF}	Diff.	S.E. of diff	β_{DR}	Diff.	S.E. of diff
Less than 12 months.	2.1238	-	-	-1.6766	-	-
Less than 18 months	2.4549	0.3311	(0.0548)	-1.9752	-0.2986	(0.0870)
Less than 24 months	2.7279	0.2730	(0.0523)	-2.2216	-0.2464	(0.0663)
Less than 30 months	2.9978	0.2699	(0.0529)	-2.4653	-0.2437	(0.0939)
Less than 36 months	3.1435	0.1457	(0.0512)	-2.5991	-0.1338	(0.0552)
Less than 42 months	3.2509	0.1074	(0.0601)	-2.6991	-0.1000	(0.0831)
Less than 48 months	3.4010	0.1501	(0.0501)	-2.8330	-0.1339	(0.0691)
Less than 54 months	3.4782	0.0772	(0.0640)	-2.9044	-0.0714	(0.0910)
Less than 60 months	3.6308	0.1527	(0.0965)	-3.0375	-0.1331	(0.1885)
Less than 120 months	3.9967	0.3659	(0.1654)	-3.3794	-0.3418	(0.2334)

Table 2: Variances of cash flow news and discount rate news of the market portfolio

We report the variances of the cash flow news and discount rate news, and their covariances for the equity market portfolio. The plus signs indicate the state variables that are included in the VAR model. Excess return refers to that of the equity market portfolio; term spread is the spread of the long-term over short-term taxable bond yield; PE is the log 10-year smoothed S&P 500 price-earning ratio; VS is the value spread; PE 1yr is the log one-year smoothed S&P 500 price-earning ratio; dividend yield refers to that of the market portfolio; Book-to-market is that of the Dow Jones Industrial average; BM is the book-to-market spread; stock variance is the sum of squared daily returns of S&P 500; corporate issue is the ratio of 12-month moving sums of net issues of NYSE listed stocks divided by the market capitalization of NYSE stocks.

	Models							
	1	2	3	4	5	6	7	8
Excess return	+	+	+	+	+	+	+	+
Term spread	+	+	+	+	+	+	+	+
PE ratio	+							
Value spread	+	+	+	+	+	+	+	+
PE 1yr			+					+
Dividend yield				+				
Book-to-market ratio					+			+
BM spread						+	+	
Stock variance								+
Corporate issue							+	+
Panel A: Monthly data (1929-2001)								
Variance of CF	0.06%	0.44%	0.09%	0.14%	0.10%	0.36%	0.57%	0.09%
Variance of DR	0.27%	0.05%	0.16%	0.12%	0.21%	0.10%	0.30%	0.24%
Cov(CF, DR)	0.01%	0.09%	-0.02%	-0.02%	0.01%	0.08%	0.28%	0.02%
Panel B: Monthly data (1952-2001)								
Variance of CF	0.04%	0.21%	0.08%	0.04%	0.11%	0.20%	0.21%	0.07%
Variance of DR	0.09%	0.02%	0.06%	0.12%	0.04%	0.02%	0.06%	0.06%
Cov(CF, DR)	-0.02%	0.03%	-0.02%	-0.01%	-0.02%	0.02%	0.05%	-0.02%
Panel C: Annual data (1931-2001)								
Variance of CF	0.30%	2.56%	1.31%	1.62%	0.91%	2.91%	2.59%	1.04%
Variance of DR	2.66%	0.04%	1.54%	2.19%	1.36%	0.29%	0.41%	1.74%
Cov(CF, DR)	0.14%	-0.19%	0.04%	0.55%	-0.29%	0.29%	0.21%	0.01%
Panel D: Annual data (1952-2001)								
Variance of CF	0.33%	2.30%	0.94%	0.47%	1.29%	2.64%	2.50%	0.98%
Variance of DR	1.32%	0.17%	1.33%	1.98%	0.50%	0.28%	0.50%	1.19%
Cov(CF, DR)	-0.46%	-0.07%	-0.15%	-0.01%	-0.42%	0.16%	0.23%	-0.14%

Table 3: CAPM beta, cash flow beta, and discount rate beta

We use the same dataset as in Campbell and Vuolteenaho (2004A). Panel A reports, for both the pre-1963 and post-1963 periods, the CAPM betas, cash flow betas, and discount rate betas of 25 Fama-French portfolios sorted by size and the market-to-book ratio. The same state variables in Campbell and Vuolteenaho (2004A) are used to obtain the cash flow betas and discount rate betas. In Panel B average returns of portfolios, including the 25 Fama-French portfolios and 20 additional portfolios as in Campbell and Vuolteenaho (2004A), are first obtained, and are then regressed cross-sectionally on the betas.

Panel A: CAPM beta, cash flow beta, and discount rate beta

	Before 1963:6					After 1963:7				
β_{CAPM}	Growth	2	3	4	Value	Growth	2	3	4	Value
Small	1.73	1.65	1.54	1.46	1.56	1.43	1.22	1.08	1.00	1.01
2	1.15	1.28	1.26	1.34	1.50	1.42	1.16	1.03	0.97	1.04
3	1.21	1.14	1.21	1.24	1.56	1.36	1.10	0.97	0.89	0.97
4	0.97	1.10	1.14	1.30	1.67	1.25	1.07	0.96	0.89	0.97
Large	0.95	1.92	1.04	1.29	1.48	1.00	0.94	0.84	0.77	0.77
β_{CF}										
Small	0.58	0.51	0.43	0.46	0.55	0.05	0.06	0.08	0.09	0.13
2	0.30	0.36	0.39	0.41	0.49	0.03	0.08	0.10	0.11	0.12
3	0.32	0.29	0.32	0.37	0.51	0.03	0.09	0.10	0.12	0.12
4	0.20	0.27	0.32	0.37	0.53	0.02	0.09	0.11	0.11	0.13
Large	0.20	0.19	0.29	0.34	0.42	0.02	0.08	0.08	0.11	0.11
β_{DR}										
Small	1.37	1.63	1.41	1.37	1.39	1.63	1.35	1.17	1.11	1.11
2	1.04	1.20	1.16	1.20	1.30	1.51	1.20	1.05	0.94	1.01
3	1.16	1.02	1.09	1.08	1.32	1.39	1.08	0.94	0.82	0.93
4	0.86	0.99	1.00	1.10	1.41	1.25	1.03	0.87	0.78	0.86
Large	0.87	0.82	0.89	1.07	1.19	1.00	0.86	0.73	0.63	0.67

Panel B: The cross-section of equity returns

CAPM						
	Intercept	β	Adj. R^2	Intercept	β	Adj. R^2
Coeff.	0.26%	0.54%	40.13%	0.80%	-0.18%	2.10%
S.E.	(0.13%)	(0.10%)		(0.14%)	(0.13%)	

TwoBeta ICAPM							
	Intercept	β_{CF}	β_{DR}	Adj. R^2	Intercept	β_{CF}	β_{DR}	Adj. R^2
Coeff.	0.42%	1.24%	0.10%	44.76%	0.07%	5.30%	0.10%	49.99%
S.E.	(0.15%)	(0.66%)	(0.31%)		(0.13%)	(0.80%)	(0.08%)	

Table 4: Betas with a subset or similar state variables

Campbell and Vuolteenaho (2004A) use four state variables in their VAR system: excess equity market return, term spread, 10-year smoothed PE ratio, and the value spread. To examine the robustness, we choose a subset of these variables (exluding the PE ratio) in Panel A, and use similar variables to replace the 10-year smoothed PE ratio in Panels B1-B5. In particular, we replace the 10-year smoothed PE ratio by a 1-year smoothed PE ratio in Panel B1, by the market dividend yield in Panel B2, by the Dow Jones book-to-market ratio in Panel B3, by the book-to-market ratio of value stocks, together with corporate issue, in Panel B4, and by the updated 10-year smoothed PE ratio in Panel B5. In each case we first report the trends and magnitude of betas. The standard errors of the differences of the betas between large and small as well as value and growth firms are obtained through bootstrapping 2500 realizations. In Panel A we also report the cross-sectional regressions, where γ, the risk-aversion coefficient, is equal to the ratio of the coefficient on the cash flow beta and on the discount rate beta. This table only reports results during the period 1963:7 - 2001:12.

Panel A: VAR variables include the excess equity market return, term spread, and value spread

Panel B1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
Small	1.74		1.51		1.39		1.35		1.44		-0.30	[0.07]
2	1.63		1.45		1.34		1.25		1.35		-0.28	[0.07]
3	1.54		1.36		1.23		1.15		1.26		-0.28	[0.08]
4	1.37		1.29		1.17		1.07		1.20		-0.17	[0.08]
Large	1.09		1.09		0.95		0.91		0.97		-0.12	[0.08]
Diff	-0.65	[0.12]	-0.42	[0.10]	-0.44	[0.10]	-0.44	[0.09]	-0.47	[0.09]		

β_{DR}	Growth	2	3	4	Value	Diff	
Small	-0.03	-0.07	-0.12	-0.13	-0.18	0.15	[0.05]
2	-0.05	-0.14	-0.16	-0.17	-0.19	0.14	[0.04]
3	-0.08	-0.15	-0.16	-0.19	-0.19	0.11	[0.05]
4	-0.06	-0.15	-0.16	-0.15	-0.19	0.13	[0.05]
Large	-0.05	-0.12	-0.11	-0.15	-0.17	0.12	[0.04]
Diff	0.02 [0.07]	0.05 [0.07]	-0.01 [0.06]	0.02 [0.06]	0.01 [0.05]		

Panel A2: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	-0.04%	0.16%	-3.65%	52.36%	-0.0432
S.E.	(0.14%)	(0.08%)	(0.51%)		

Table 4: Continued – Cash flow betas

β_{CF}	Growth		2		3		4		Value		Diff	
Panel B1: VAR variables include the excess equity market return, term spread, log 1-year PE ratio, and value spread												
Small	0.58		0.49		0.44		0.43		0.46		-0.12	[0.05]
2	0.52		0.47		0.42		0.38		0.42		-0.10	[0.05]
3	0.48		0.42		0.39		0.36		0.39		-0.09	[0.06]
4	0.44		0.41		0.38		0.33		0.38		-0.06	[0.05]
Large	0.32		0.35		0.30		0.29		0.30		-0.02	[0.05]
Diff	-0.26	[0.08]	-0.14	[0.07]	-0.14	[0.06]	-0.14	[0.06]	-0.16	[0.06]		
Panel B2: VAR variables include the excess equity market return, term spread, dividend yield, and value spread												
Small	0.98		0.87		0.81		0.80		0.87		-0.11	[0.07]
2	0.91		0.84		0.80		0.76		0.83		-008	[0.07]
3	0.87		0.81		0.74		0.71		0.77		-0.10	[0.07]
4	0.77		0.77		0.71		0.66		0.74		-0.03	[0.07]
Large	0.63		0.66		0.58		0.58		0.61		-0.02	[0.07]
Diff	-0.35	[0.11]	-0.21	[0.09]	-0.23	[0.08]	-0.22	[0.08]	-0.26	[0.08]		
Panel B3: VAR variables include the excess equity market return, term spread, Dow Jones book-to-market ratio, and value spread												
Small	0.72		0.59		0.52		0.52		0.55		-0.17	[0.08]
2	0.63		0.54		0.50		0.48		0.52		-0.11	[0.08]
3	0.59		0.51		0.46		0.44		0.47		-0.12	[0.08]
4	0.53		0.48		0.44		0.39		0.43		-0.10	[0.08]
Large	0.42		0.42		0.36		0.35		0.36		-0.06	[0.07]
Diff	-0.30	[0.11]	-0.17	[0.10]	-0.16	[0.09]	-0.17	[0.08]	-0.19	0.08]		
Panel B4: VAR variables include the excess equity market return, term spread, book-to-market of value stocks, corporate issue, and value spread												
Small	0.64		0.52		0.46		0.47		0.50		-0.14	[0.08]
2	0.55		0.48		0.45		0.43		0.48		-0.07	[0.08]
3	0.53		0.47		0.41		0.39		0.44		-0.09	0.08]
4	0.46		0.44		0.40		0.34		0.39		-0.07	[0.08]
Large	0.38		0.39		0.33		0.31		0.33		-0.05	[0.07]
Diff	-0.26	[0.12]	-0.13	[0.10]	-0.13	[0.09]	-0.16	[0.08]	-0.17	[0.08]		
Panel B5: VAR variables include the excess equity market return, term spread, updated 10-year smoothed PE ratio, and value spread												
Small	1.35		1.15		1.01		0.97		0.99		-0.36	[0.04]
2	1.26		1.04		0.94		0.86		0.93		-0.33	[0.04]
3	1.18		0.96		0.85		0.77		0.86		0.32	[0.04]
4	1.06		0.91		0.80		0.73		0.81		-0.25	[0.04]
Large	0.87		0.78		0.67		0.61		0.65		-0.22	[0.04]
Diff	-0.48	[0.07]	-0.37	[0.06]	-0.34	[0.05]	-0.36	[0.05]	-0.34	[0.05]		

Table 5: Betas with additional state variables

We study the cross-sectional pattern of cash flow betas when alternative specfications are used. In Panel A we use the state variables by Petkova (2004) that provide intuitive interpretations on Fama-French factors. In Panel B we add variables shown by Lettau and Ludvigson (2001) and Ludvigson and Ng (2005) to exhibit good predictive power for equity returns. Panel B uses quarterly data because these variables are available only at quarterly frequency. We present results only for the 1963-2001 period.

β_{CF}	Growth		2		3		4		Value		Diff	
Panel A: VAR variables: excess equity market return, term yield, dividend yield, credit spread, and risk-free rate (Petkova (2004))												
Small	1.47		1.28		1.18		1.14		1.18		-0.29	[0.07]
2	1.39		1.23		1.13		1.08		1.12		-0.27	[0.08]
3	1.34		1.15		1.05		0.96		1.04		-0.30	[0.08]
4	1.21		1.07		0.99		0.93		1.02		-0.19	[0.08]
Large	0.93		0.91		0.77		0.74		0.77		-0.16	[0.08]
Diff	-0.54	[0.12]	-0.37	[0.09]	-0.41	[0.09]	-0.40	[0.08]	-0.41	[0.08]		
Panel B: VAR variables include excess equity market return, term spread, PE ratio, value spread, cay, risk-premium factor, and volatility factor												
Small	0.48		0.43		0.40		0.40		0.44		-0.04	[0.19]
2	0.40		0.37		0.38		0.35		0.39		-0.01	[0.19]
3	0.35		0.34		0.32		0.33		0.36		0.01	[0.20]
4	0.33		0.32		0.32		0.32		0.35		0.02	[0.19]
Large	0.24		0.25		0.26		0.25		0.22		-0.02	[0.18]
Diff	-0.24	[0.25]	-0.18	[0.22]	-0.14	[0.19]	-0.15	[0.18]	-0.22	[0.18]		

Table 6: Betas when cash flow news is directly modelled

We directly model both the discount rate news and cash flow news using two separate VAR systems. To avoid cash flow seasonality all variables are converted into annual frequency. The VAR to predict the discount rate include the same variables as in the benchmark case. We use two cash flow proxies: dividend growth rate and earning return on book equity (ROE). The VAR to predict dividend growth rate includes dividend growth rate, market equity return, and dividend yield; the VAR to predict ROE include ROE, market equity return, and book-to-market. For both cash flow measures, we further decompose the cash flow news into two components. The first is the residual of the cash flow prediction from the cash flow VAR, which we call the current component. The second is the rest of the cash flow news that considers the future combined impact of the current innovation on the value of equity. Because we directly model both cash flow and discount rate news, they will not add up exactly to the return news, leaving a noise component. For all four news components – the current and future cash flow news, the discount rate news, and the news noise – we present the cross-sectional betas. In addition, we present the cash flow beta (i.e., the sum of the current and future cash flow betas) plus the noise beta, which is equivalent to the cash flow beta if we model only the discount rate news but back out the cash flow news as the residual. Similarly, we also present the discount rate beta plus the noise beta, which is equivalent to the discount rate beta if we model only the cash flow news but back out the discount rate news as the residual. Panel A report the case for dividend growth rate; Panel B report the case for ROE.

Panel A: Dividend growth rate as the cash flow proxy

	Growth	2	3	4	Value	Growth	2	3	4	Value
	$\beta_{CF_Current}$					β_{CF_Future}				
Small	0.54	0.35	0.27	0.21	0.29	0.51	0.43	0.38	0.35	0.37
2	0.42	0.32	0.23	0.26	0.26	0.48	0.35	0.36	0.32	0.31
3	0.35	0.25	0.21	0.24	0.19	0.47	0.39	0.34	0.33	0.30
4	0.21	0.20	0.18	0.18	0.26	0.45	0.41	0.31	0.32	0.35
Large	0.10	0.18	0.14	0.17	0.12	0.44	0.36	0.36	0.31	0.37
	β_{DR}					β_{Noise}				
Small	0.84	0.69	0.59	0.55	0.45	-0.94	-0.63	-0.47	-0.36	-0.43
2	0.80	0.52	0.56	0.40	0.36	-0.88	-0.58	-0.48	-0.45	-0.39
3	0.82	0.62	0.50	0.48	0.41	-0.88	-0.57	-0.45	-0.45	-0.33
4	0.97	0.74	0.52	0.58	0.55	-0.75	-0.57	-0.41	-0.43	-0.55
Large	0.99	0.69	0.66	0.54	0.61	-0.65	-0.59	-0.50	-0.45	-0.45
	$\beta_{CF} + \beta_{Noise}$					$\beta_{DR} + \beta_{Noise}$				
Small	0.10	0.16	0.17	0.20	0.23	-0.11	0.06	0.11	0.18	0.02
2	0.02	0.09	0.11	0.14	0.18	-0.07	-0.06	0.08	-0.05	-0.04
3	-0.06	0.07	0.10	0.12	0.16	-0.05	0.05	0.05	0.02	0.08
4	-0.09	0.04	0.09	0.06	0.06	0.22	0.17	0.11	0.16	-0.00
Large	-0.11	-0.06	0.00	0.02	0.05	0.34	0.10	0.16	0.08	0.16

Table 6 – Continued

Panel B: ROE as the cash flow proxy

	Growth	2	3	4	Value	Growth	2	3	4	Value
	$\beta_{CF_Current}$					β_{CF_Future}				
Small	0.05	0.03	0.02	0.01	-0.02	0.39	0.34	0.29	0.26	0.24
2	0.03	0.02	-0.02	0.00	-0.02	0.37	0.25	0.25	0.22	0.19
3	-0.02	0.00	0.01	0.00	-0.01	0.34	0.29	0.26	0.24	0.21
4	-0.01	0.01	0.01	0.00	-0.03	0.36	0.33	0.25	0.25	0.23
Large	-0.06	-.02	-0.02	-0.01	-0.09	0.32	0.26	0.27	0.22	0.22
	β_{DR}					β_{Noise}				
Small	0.79	0.67	0.58	0.53	0.47	-0.29	-0.18	-0.12	-0.06	0.02
2	0.80	0.52	0.58	0.41	0.37	-0.31	-0.16	-0.10	-0.07	0.02
3	0.86	0.64	0.52	0.49	0.42	-0.31	-0.20	-0.14	-0.11	-0.03
4	0.98	0.76	0.53	0.57	0.57	-0.38	-0.25	-0.16	-0.17	-0.13
Large	1.01	0.71	0.70	0.55	0.68	-0.30	-0.26	-0.21	-0.16	-0.06
	$\beta_{CF}+\beta_{Noise}$					$\beta_{DR}+\beta_{Noise}$				
Small	0.16	0.18	0.18	0.21	0.23	0.51	0.50	0.45	0.47	0.49
2	0.08	0.11	0.13	0.14	0.19	0.49	0.36	0.48	0.33	0.39
3	0.01	0.09	0.12	0.13	0.17	0.55	0.44	0.38	0.37	0.40
4	-0.03	0.08	0.10	0.08	0.08	0.60	0.50	0.36	0.40	0.44
Large	-0.04	-0.01	0.05	0.05	0.07	0.71	0.46	0.49	0.39	0.61

Table 7: Is cash flow beta priced in industry portfolios ?

Using the same state variables as in Campbell and Vuolteenaho (2004A), we calculate cash flow and discount rate betas for 48 industry portfolios (Fama and French (1997)). In Panel A we first group the portfolios by the magnitude of the two betas, and then report the average returns in each cell. Note there is no portfolio belonging to the low DR beta/3rd CF beta cell. In Panel B we report the cross-sectional regression of the average returns on the betas. This table reports cash flow and discount rate betas only during the period 1963:7 - 2001:12.

Panel A: Average returns

	Cash flow beta			
Discount rate beta	Low	2	3	High
Low	0.58%	0.61%	-	0.52%
2	0.76%	0.57%	0.22%	0.31%
3	0.43%	0.51%	0.43%	0.33%
High	0.65%	0.75%	0.32%	0.29%

Panel B: Cross-sectional regression

	Intercept	Cash flow beta	Discount rate beta	Adj. R^2	γ
Coefficient	0.44%	-3.83%	-0.03%	19.41%	149.0403
Standard deviation	(0.19%)	(1.05%0	(0.12%)		

Table 8: Betas when the VAR coefficients are estimated using post-1952 data

In Campbell and Vuolteenaho (2004A), cash flow (discount rate) betas are estimated using a VAR model over the full 1929:1-2001:12 period. This table estimate cash flow (discount rate) betas using a VAR model over the 1952:01 - 2001:12 period. We use the same state variables as in Campbell and Vuolteenaho (2004A). We report the trends and magnitude of betas. The standard errors of the differences of the betas between large and small and value and growth firms are obtained through bootstrapping 2500 realizations. This table reports only cash flow and discount rate betas during the 1963:7 - 2001:12 period.

β_{CF}	Growth		2		3		4		Value		Diff	
Small	0.64		0.53		0.48		0.46		0.48		-0.16	[0.09]
2	0.58		0.49		0.44		0.40		0.43		-0.15	[0.08]
3	0.53		0.45		0.40		0.36		0.40		-0.13	[0.09]
4	0.47		0.43		0.38		0.34		0.38		-0.09	[0.08]
Large	0.36		0.35		0.31		0.29		0.30		-0.06	[0.08]
Diff	-0.28	[0.10]	-0.18	[0.09]	-0.17	[0.08]	-0.17	[0.07]	-0.18	[0.07]		

β_{DR}	Growth		2		3		4		Value		Diff	
Small	1.09		0.92		0.81		0.78		0.80		-0.29	[0.08]
2	1.01		0.83		0.74		0.68		0.74		-0.27	[0.07]
3	0.94		0.76		0.67		0.60		0.68		-0.26	[0.08]
4	0.84		0.72		0.63		0.57		0.64		-0.20	[0.07]
Large	0.68		0.61		0.52		0.47		0.51		-0.17	[0.06]
Diff	-0.41	[0.09]	-0.31	[0.07]	-0.29	[0.06]	-0.31	[0.06]	-0.29	[0.06]		

Table 9: Long-Term Betas

Panel A reports the cumulative CAPM beta of portfolio excess return on market equity excess return from 1-year to 15-year horizons. Panel B reports the cumulative consumption beta of portfolio excess return on consumption growth from 1-year to 15-year horizons. In both panels we include Newey-West standard errors in the brackets controlling for heteroskedasticity and autocorrelation.

Panel A: CAPM beta										
	Growth		2		3		4		Value	
Panel A1: 1 year										
Small	1.45	[0.16]	1.36	[0.15]	1.23	[0.15]	1.21	[0.15]	1.29	[0.14]
2	1.34	[0.09]	1.20	[0.11]	1.13	[0.10]	1.11	[0.12]	1.20	[0.14]
3	1.24	[0.09]	1.08	[0.09]	1.05	[0.10]	1.02	[0.09]	1.10	[0.14]
4	0.99	[0.07]	1.00	[0.09]	0.99	[0.09]	1.00	[0.11]	1.13	[0.13]
Large	0.91	[0.04]	0.82	[0.03]	0.83	[0.05]	0.92	[0.09]	1.03	[0.09]
Panel A2: 10 years										
Small	0.40	[0.16]	0.40	[0.16]	0.54	[0.17]	0.45	[0.12]	0.54	[0.15]
2	0.73	[0.14]	0.63	[0.15]	0.52	[0.10]	0.38	[0.14]	0.49	[0.13]
3	0.77	[0.12]	0.55	[0.12]	0.62	[0.10]	0.50	[0.07]	0.44	[0.14]
4	0.68	[0.10]	0.75	[0.11]	0.61	[0.07]	0.39	[0.05]	0.57	[0.15]
Large	0.74	[0.09]	0.56	[0.09]	0.76	[0.07]	0.62	[0.08]	0.63	[0.09]
Panel A3: 15 years										
Small	0.39	[0.11]	0.36	[0.10]	0.52	[0.10]	0.44	[0.07]	0.54	[0.10]
2	0.71	[0.10]	0.62	[0.10]	0.50	[0.06]	0.36	[0.09]	0.48	[0.09]
3	0.74	[0.08]	0.53	[0.08]	0.60	[0.07]	0.49	[0.04]	0.41	[0.08]
4	0.65	[0.08]	0.73	[0.07]	0.60	[0.05]	0.38	[0.03]	0.57	[0.09]
Large	0.71	[0.08]	0.53	[0.08]	0.75	[0.06]	0.61	[0.05]	0.62	[0.06]

Table 9 – Continued

Panel B: Consumption beta										
	Growth		2		3		4		Value	
Panel A1: 1 year										
Small	0.24	[1.25]	1.44	[1.65]	-0.08	[1.46]	-0.01	[1.81]	-0.75	[1.87]
2	1.34	[1.33]	0.87	[1.75]	-1.15	[1.42]	-1.13	[1.59]	0.36	[1.53]
3	-0.45	[1.55]	0.30	[1.45]	1.11	[1.45]	0.80	[1.27]	0.27	[1.72]
4	-0.44	[1.02]	-0.15	[1.33]	0.27	[1.41]	-0.60	[1.56]	-0.68	[1.89]
Large	0.49	[0.94]	0.14	[0.91]	0.97	[1.22]	0.77	[1.56]	-1.31	[1.46]
Panel A2: 10 years										
Small	4.75	[3.06]	-0.51	[1.54]	0.18	[2.15]	0.58	[1.50]	1.93	[2.00]
2	3.91	[2.61]	1.67	[2.35]	0.86	[1.17]	-0.06	[1.42]	2.39	[1.73]
3	0.91	[1.92]	1.05	[1.55]	0.89	[1.98]	2.23	[1.34]	-0.34	[1.63]
4	-0.25	[1.76]	-0.41	[2.07]	0.90	[1.65]	1.38	[0.96]	-0.98	[1.87]
Large	0.05	[2.69]	-2.60	[2.14]	0.88	[2.28]	-0.02	[1.94]	0.32	[2.01]
Panel A3: 15 years										
Small	8.12	[1.75]	0.59	[1.42]	1.02	[2.43]	1.61	[1.73]	3.61	[2.43]
2	5.22	[3.04]	2.99	[2.74]	1.51	[1.77]	0.33	[1.63]	3.83	[2.11]
3	2.82	[2.46]	1.72	[1.99]	2.47	[2.48]	3.16	[1.63]	-0.23	[2.04]
4	0.66	[2.06]	1.32	[2.52]	3.09	[2.01]	2.39	[1.13]	1.60	[2.50]
Large	1.34	[2.41]	-1.40	[2.07]	3.13	[2.38]	1.61	[2.49]	1.14	[2.23]

Figure 1: Log 10-year PE Ratios

We plot the log 10-year PE ratio from Campbell and Vuolteenaho (2004) and from Robert Shiller (both available online) for the 1929:1-2001:12 period. The correlation for the two time series is 92%.

