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

First version: April 2005
Current version: February 2006

Abstract

We study the robustness of the return decomposition approach, in which the unexpected equity return is decomposed into the discount rate (DR) news and the 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. It has been documented using this approach that the variation of the market portfolio return is mainly driven by the discount rate news; and that value stocks earn higher returns because they have higher cash flow betas. 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 cash flow variance and zero cash flow betas. In contrast, we find that the variance of the "cash flow news" is larger than that of the discount rate news; and that bonds with longer maturities have higher "cash flow betas." Applying the approach to equity returns, we show that, for many of the forecasting-variable specifications, the variance of the cash flow news is usually no smaller than that of the discount rate news; and that value stocks usually do not have higher cash flow betas. Finally, we decompose the cash flow 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.

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

*We are grateful to Geoff Booth, John Campbell, Murillo Campello, Hui Guo, Raymond Kan, Sydney Ludvigson, Chao Wei, Lu Zhang and seminar participants at Michigan State University for their very helpful comments. We are responsible for all remaining errors.

1 Introduction

The seminal work by Campbell and Shiller (1988a, 1988b) 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 (2004) 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:

- For the equity market portfolio, the variance of the DR news is larger than the variance of the CF news, 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 return at the aggregate level is mainly driven by the time-varying risk premium.

- In a recent influential paper, Campbell and Vuolteenaho (2004) find that, for 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 fake 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 model 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 inference 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 CF uncertainty; the estimated "CF news" contains no actual CF news but is pure modeling noise.[1] They 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 fake 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. Following the current literature, we investigate a list of state variables that have been shown to forecast equity returns, including the term spread (difference between long-term and short-term bond yield), the price-earning (PE) ratio, the value spread (log

[1] Note 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. For Treasury securities, however, inflation shocks can only affect the discount rate. Accordingly, nominal interest rate reflects expected inflation but bond cash flows are fixed. When we apply the return decomposition according to bond present value formula there must be no cash flow risk.

book-to-market of value stocks minus that of growth stocks), the credit spread (Baa over Aaa yield), the dividend yield (dividend-price ratio), the book-to-market spread (the book-to-market of value stocks minus that of growth stocks), the market-to-book spread (the market-to-book of growth stocks minus that of value stocks), the riskfree rate, *cay* from Lettau and Ludvigson (2001), and the risk premium factor and the volatility factor from Ludvigson and Ng (2005). The first three variables are used in Campbell and Vuolteenaho (2004), which we call the benchmark case. We also use the same dataset as in Campbell and Vuolteenaho (2004) for direct comparison.[2] The following general patterns can be summarized among the variables into which we looked:

First, the benchmark case is sensitive to updates, to close substitutions, or to sample periods. In particular, one state variable in the benchmark case, the 10-year smoothed PE ratio, is from Shiller (2000), which has been updated by Shiller. Once we replace the old PE ratio with the new one, even though they are highly correlated, the CF beta trend from growth to value stocks is reversed for the same sample period of the benchmark case. We reach the same conclusion if we replace the old 10-year smoothed PE ratio with the 1-year or 2-year PE ratio. In addition, if we replace the PE ratio by the dividend yield – it is reasonable to expect that they convey similar information regarding the discount rate – then the original cash flow beta trend disappears.[3] Furthermore, we apply the return decomposition to the post-1963 period (instead of the full 1929:1-2001:12 period) because CAPM breaks down in this period (see Ang and Chen (2005) and Fama and French (2005). We find that value stocks have lower CF betas.

Second, the benchmark case is sensitive to addition or subtraction of variables. In order for value stocks to have higher CF betas than growth stocks do, both the PE ratio and the value spread need to be included. If, say, the PE ratio is missing, then no matter what other variables are included, we usually find that value stocks have either significantly lower or no higher CF betas than growth stocks. For example, among the three benchmark case variables, if we use (i) any of them alone, (ii) the term spread and the PE ratio, or (iii) the term spread and the value spread, we always find that value stocks have lower CF betas. Additional variables from the list we cited above generally do not change these patterns. Furthermore, even if both the PE ratio and the value spread are included, once we also include dividend yield and credit spread – two of the most

[2] We thank the authors for kindly providing the data.

[3] Shiller (1984) and Fama and French (1988) find that the dividend yield predicts equity return better than the earning price ratio does. Note it cannot be argued here that the PE ratio is preferred to dividend yield because it is more stationary. We find, instead, that the 10-year smoothed PE ratio is clearly unstationary according to augmented Dicky-Fuller tests. Regressing this variable on its own lag yields a coefficient of 0.99 and an R-square of 0.98 (see also Table 2 of Campbell and Vuolteenaho (2004)). In comparison, the dividend yield we use rejects the null of unstationarity with a p-value of 0.08.

commonly used forecasting variables – then the beta trend disappears.[4] Simply put, for most of the combinations of the above state variables that predict equity returns, value stocks do not have higher CF betas.[5]

Third, the CF beta trend from stock to value stocks is sensitive to alternative model specifications. While we experiment with many, we only present three cases: (i) the state variables used in Petkova (2004) that can intuitively explain the Fama-French factors; (ii) the inclusion of the risk premium factor and the volatility factor from Ludvigson and Ng (2005) that can largely increase the predictive power of equity returns; and (iii) the inclusion of the book-to-market spread and the market-to-book spread (Liu and Zhang (2005)) that can largely increase the cross-sectional explanatory power of equity returns. In all cases we find that the CF beta trend is either reversed or disappears.

Fourth, 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. 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 variances of the DR news and the CF news, as well as the relative magnitude of the DR betas and CF betas, vary in a fashion similar to the cross-sectional pattern of the betas, depending on what state variables are included. For example, the proportion of total variance that the CF variance represents ranges from 18% to 97% when different state variables are chosen. Therefore, we could easily conclude that, for the market portfolio, the variance of the CF news outweighs the variance of the DR news, or vice versa. The pattern holds for both the pre- and post-1963 periods.

To summarize, many studies in the return decomposition literature choose state variables based on their priors; subsequently, only limited attention has been given to the sensitivity of these choices. For example, Campbell and Vuolteenaho (2004) 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). Because their objective is to examine results based on their priors, they do not explore as many alternative state variables as we do.

[4] Lamont (1998) show that both PE ratio and dividend yield can be used together to predict equity returns.

[5] Campbell and Vuolteenaho (2004) emphasize that the inclusion of the value spread is important. We find that, if the PE ratio is not considered, then a combination the value spread and other state variables usually leads to a conclusion opposite to that in Campbell and Vuolteenaho (2004).

Instead, we focus on the sensitivity of the return decomposition approach with respect to the choice of state variables. We provide a clear theoretical rationale on why this aspect of the robustness check could be vital. Confirming our prior by investigating both Treasury bond returns and equity returns, we find that the major conclusions based on the comparison of the DR news and CF news – the relative variances, the magnitude of betas, and the cross-sectional patterns – could all be sensitive to the choice of the state variables. We conclude that serious caution needs to be exercised when interpreting the results from this approach.

A natural question is whether the results in the current literature can be resurrected 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.[6] 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.

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. Section 5 provides robustness checks, and 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, 1988b). Campbell (1991) further provides the following decomposition of the unexpected return:

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

[6] Introducing cdy, which is shown by Lettau and Ludvigson (2005) to possess good predictive power for the dividend growth rate, does not change the conclusions we draw.

where $r_{t+1}$is the equity return and E_t is the expectation operator at time t, ρ is a number close to but lower than 1, and Δd_t is the dividend growth rate. We decompose the market portfolio following Campbell and Vuolteenaho (2004). 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

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

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

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

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 (2004) 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

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

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

$$\begin{aligned} \beta_{i,CF} &\equiv \left(e1' + e1'\lambda\right) \frac{Cov\left(e_{i,t}, u_t\right)}{Var\left(e\right)}, && (8) \\ \beta_{i,DR} &\equiv -e1'\lambda \frac{Cov\left(e_{i,t}, u_t\right)}{Var\left(e\right)}, && (9) \end{aligned}$$

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

Following Campbell and Vuolteenaho (2004), 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 (2004) 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 bigger than one (e.g., γ is between 7.5 and 10 in Bansal and Yaron (2004)). For this reason, Campbell and Vuolteenaho (2004) call the CF beta the "bad beta" and the DR beta the "good beta". 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

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

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.[7] 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).

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

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 $cov\,(e_{i,t}, u_{2,t}) = 0$. Then it can be easily shown that

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

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

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

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

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

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 true because equity return has positive autocorrelation (see Campbell and Vuolteenaho (2004)). 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.[8] 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 a 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, 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.[9] 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 (2004), and Koubouros, Malliaropulos, and Panopoulou (2004) estimate the CF betas; Hecht and Vuolteenaho (2006) use residual-based cash flow proxies to study equity returns; in the macroeconomics literature, 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 component.

This study only concerns the corresponding parts of these studies – they also explore many

[8] 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.

[9] 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.

aspects of interesting economic implications that are outside of our concern.[10] 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 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 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 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 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

[10] 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.

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):

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

It then follows that

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

where $\lambda_2 = \left(\Gamma - \Gamma^N\right)(I - \Gamma)^{-1}$.[11] 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.

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 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 (2004) for a similar argument for equities with remote cash flows).

Table 1 about here

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.[12] 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).[13] The expected real interest rate and inflation

[11] 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.

[12] 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.

[13] 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).

are estimated following Fama and Gibbons (1982).[14]

The R-square of the VAR regression for the bond prediction equation is about 2.7%, which is very close to that of the equity prediction equation in Campbell and Vuolteenaho (2004) (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-squares in the bond and equity 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, 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 Fama-Bliss zero-coupon bond monthly return data 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

[14] 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.

patterns are false, because Treasury bonds have no 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 (2004): 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. (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.[15] We show in Table A1 the cases when nominal bond returns are used. The inferences are similar to those drawn from using excess bond returns in Table 1.

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-square, 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, for equities we examine the robustness of the current conclusions when different state variables are included. In the latter part of the paper we also attempt to model both DR and CF directly in an effort to separate actual CF news from modeling noise.

[15] The results are available upon request.

As we did with the bond market, we look into three issues in the equity market when the information set changes: (i) the relative magnitude of the two betas, (ii) the cross-sectional patterns of the two betas, and (iii) the relative variances of the CF news and DR news.

4.1 The relative magnitude of the two betas

4.1.1 The benchmark case

We use the same dataset used in Campbell and Vuolteenaho (2004) to make direct comparison. Campbell and Vuolteenaho (2004) 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 CF betas and DR betas do so very successfully.

Table 2 is a brief replication of what is achieved in Campbell and Vuolteenaho (2004). 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.

Table 2 about here

The CF betas and DR betas we calculate are very close to those in Campbell and Vuolteenaho (2004).[16] 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

[16] We find that our decomposed CF news and DR news are identical to those in Campbell and Vuolteenaho (2004) (available on Professor 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.

firms. Combined, they explain 50% of the variation, compared to the meager 2% for the CAPM model. Based on the evidence, Campbell and Vuolteenaho (2004) 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.

4.1.2 Subsets of the state variables in the benchmark case and similar variables

Campbell and Vuolteenaho (2004) use four state variables in their VAR system: excess equity market return, the term spread, the PE ratio, and 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. We first investigate what will happen if we include only a subset of the three optional variables in the benchmark case. We also examine cases in which the PE ratio is replaced by similar variables. We focus on the post-1963 period in the rest of the paper because the CAPM breaks down in this period.

Table 3 about here

The results are presented in Table 3. The standard errors reported in the table are obtained through bootstrapping with 2500 realizations. In Panel A we include two optional state variables: the term spread and the PE ratio. We find two patterns that are drastically different from those in the benchmark case. First, the CF beta significantly declines from growth to value firms. For example, the CF beta for small growth stocks is 0.47, which shrinks to 0.32 for small value stocks. The difference of -0.15 is highly significant with a standard deviation of 0.03. The same trend holds for all other portfolios. Second, the CF beta has a negative coefficient (Panel A3) in the cross-section of equity returns. Also noteworthy is the negative risk coefficient γ at -2.63. While a negative γ is counter-intuitive – it suggests that stocks with higher CF betas should have lower risk premiums – it is frequently the case throughout the paper.

In Panel B we use the term spread and the value spread as the state variables. As in Panel A, value stocks show significantly lower CF betas. In addition, the magnitude of the CF betas is much larger than that of the DR betas. The coefficient on the CF beta is positive in the cross-sectional regression. Here we are interested in two questions. The first is whether value stocks have higher CF betas, the answer to which is "no" as is clear from Panel B. The second is whether the CF beta is properly priced in the cross-sectional regression. The answer is "yes" from Panel B. However, the positive coefficient of the CF beta does not mean that value stocks earn higher return because they have higher CF betas; in fact 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.

Panels A and B represent two subsets of the state variables in the benchmark case. We also explore other combinations. We find that the inclusion of both the PE ratio and the value spread is crucial. If either of the variables is missing, which is two-third of the possible combinations, value firms are found to have significantly lower CF betas.

We further explore the PE ratio, because of its seemingly important role in the benchmark case. In Panel C we replace the PE ratio by the dividend yield, because the dividend yield is a more commonly used proxy for the discount rate (see Campbell and Shiller (1988a) and Campbell and Mei (1993)). Shiller (1984) and Fama and French (1988) find that the dividend yield predicts equity return better than the earning price ratio does. Importantly, we also find that the PE ratio used in the benchmark case is clearly unstationary according to augmented Dicky-Fuller tests. This can be seen by regressing the variable on its own lag, which yields a coefficient of 0.99 and an R-square of 0.98 (see Table 2 of Campbell and Vuolteenaho (2004)). In comparison, the dividend yield we use rejects the null of unstationarity with a p-value of 0.08. Therefore, using the dividend yield instead of the PE ratio provides a statistical improvement. This replacement, however, leads to the pattern of the CF betas opposite to the benchmark case. There is a significantly declining trend of the CF betas from the first (growth) to the fourth (value) portfolio after controlling for size.

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.[17] The result, shown in Panel D of Table 3, indicates that the trend of the CF beta from growth stocks to value stocks is 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 well, with a correlation of 92%. How could similar PE ratios yield opposite beta patterns? When the benchmark variables are used, the estimated return prediction equation (suppressing the intercept term) is

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

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

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

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

Only the coefficient on the value spread is "largely" affected (from -0.013 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 find very similar results if 1-year or 2-year smoothed PE ratio is used. Also interesting is the fact that the R-square has dropped sharply from 50% in the benchmark case 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. This example suggests that the conclusions drawn from one set of variables could be very unstable.

4.1.3 Other state variables

The state variables in the first-stage VAR regression are meant to helping 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 and DR betas are sensitive to some of these alternative variables. We only present three cases that are representative and easy to interpret.

Table 4 about here

Panel A of Table 4 includes the set of variables from Petkova (2004) 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, both DR betas and CF betas decrease significantly from growth to value stocks. In addition, the magnitude of the CF betas is much larger than that of the DR betas and is much closer to the market beta. In the cross-sectional regression the coefficient on the CF beta is significantly positive. As explained before, this is because smaller firms have higher CF betas.

Panel B presents the case in which we can largely increase the explanatory power in the second-stage cross-sectional regression. It uses three variables in the benchmark case – the excess market return, the term spread, and the value spread – plus the following variables: the credit spread, the dividend yield, the book-to-market spread, and the market-to-book spread. The last two have been shown by Liu and Zhang (2005) to outperform the value spread. The inclusion of these variables largely increases the R-square of the cross-sectional regression to 72% (compared to the 50% in the benchmark case). Nevertheless, we again find a negative trend when moving from growth to value stocks. This trend is not significant if we compare the first and fifth portfolios (i.e., growth versus value), but is significant if we compare the first and the fourth portfolios. No matter what, we do not find value stocks to have higher CF betas.

Panel C 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*, the risk-premium factor, and the volatility factor from Ludvigson and Ng (2005) – to the benchmark case.[18] These state variables increase the R-square of the equity return prediction from 2.57% in Campbell and Vuolteenaho (2004) to 14%. Panel C indicates that the inclusion of these variables wipes out the cross-sectional patterns of the CF betas in the benchmark case.

We experiment with many other combinations of state variables in addition to the excess market return, including (i) the term spread, the value spread, the dividend yield, and the credit spread; (ii) the term spread, the PE ratio, the credit spread, and the dividend yield; (iii) the term spread, the PE ratio, the value spread, the credit spread, and the dividend yield; and (iv) the term spread, the PE ratio, the credit spread, and the dividend yield. In all these cases there is a decreasing trend of CF betas from growth to value stocks.

The general trends appear to be as follows: In order for value stocks to have higher CF betas, both the PE ratio and the value spread need to be included; omitting any of the two variables generally leads to the opposite trend. Given the important role this 10-year smoothed PE ratio plays, as we have discussed earlier, it is highly autocorrelated (99%), is unstationary, and should not be included to predict equity return. If we replace it with either the updated same variable, the 1-year or 2-year PE ratio that is less smoothed, or the 1-year dividend yield, the beta trend is reversed. In addition, even if both the PE ratio and the value spread are included, once we also add the dividend yield and the credit spread–two of the most frequently used forecasting variables in the current literature–we usually find that value stocks have lower CF betas. Adding other state variables does not generally change these patterns. Therefore, it is fair to say that for most of the state variables we investigate, value stocks do not have higher CF betas.

As for the relative magnitude of the betas, including PE ratio seems also to be essential to reaching the pattern where the DR betas are larger than the CF betas. If the PE ratio is excluded, then in almost all other combinations – including those where the dividend yield is considered – the CF betas are usually higher than, or at least not smaller than, the DR betas.

[18]We thank sydney Ludvigson for kindly providing the data.

4.2 A direct modeling of the CF news

Consistent with our theoretical prior, we have shown that the cross-sectional patterns of CF betas are sensitive to the choice of state variables. A natural question is what will happen if we model both CF and DR news directly. Such a procedure amounts to breaking the CF news in the current decomposition approach into the direct CF news and a model noise. Here we will explore this approach using two different cash flow proxies: dividend growth rate and earning on book equity (also called ROE, return on equity).

4.2.1 Dividend growth rate

We can revise our earlier log-linear approximation as follows:

$$e_{t+1} = e_{CF,t+1} - e_{DR,t+1} + residual, \tag{22}$$

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.[19] 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

$$e_{CF,t+1} = e1'\lambda_3\varpi_{t+1}, \tag{23}$$

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 estimation coefficients of the VAR system. Finally, we construct the residual component after the CF news and DR news are both considered.

<u>TABLE 5 ABOUT HERE</u>

In Panel A of Table 5 we report the betas for the 25 portfolios. The state variables in the discount 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

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

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.[20]

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 example suggests the difficulty of drawing meaningful conclusions using the residual-based return decomposition approach.

We experiment with other state variable specifications. As we have shown earlier, the DR beta usually declines from growth to value firms for most of the specifications. We also add cdy in the dividend growth rate VAR – Lettau and Ludvigson (2005) show that the variable predicts dividend growth – and find that our conclusion does not change.

In Table 5 the market portfolio is decomposed but the individual portfolios are not. To ensure robustness, we also try the other two alternatives: (i) decompose both the market and the individual portfolios; and (ii) decompose the individual portfolios but do not decompose the market portfolio. In neither case do we find that value stocks have higher directly-modeled CF betas.

4.2.2 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

[20] 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.

definition of equity return and return of equity (ROE):

$$r_t = \ln\left(\frac{M_t + D_{t+1}}{M_{t-1}}\right) \tag{24}$$

$$ROE_t = \ln\left(\frac{B_t + D_{t+1}}{B_{t-1}}\right), \tag{25}$$

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)):

$$b_t - m_t = \text{constant} + \sum_{j=1}^{\infty} \rho^{j-1} \left(r_{t+j-1} - e_{t+j-1}\right), \tag{26}$$

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

$$e_{t+1} = (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{N} \rho^j ROE_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{N} \rho^j r_{t+1+j}, \tag{27}$$

where e_{t+1} is as before the unexpected equity returns. 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 David, Fama, and French (2000). The finally created market portfolio, at annual frequency, has ROE and book-to-market available covering the 1930-2001 period. We then apply the return decomposition and report the results in Panel B of table 5.

Using ROE as the alternative cash flow measure yields the same inference as 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 results in Campbell and Vuolteenaho (2004) that value stock have higher combined betas. Again, the results in the benchmark case are driven by the residual betas.

4.2.3 Discussion

We have examined scenarios in which we can decompose the market portfolio and/or the individual portfolios. So long as the cash flow measures are not backed out as residuals, we do not find that value firms have higher directly-modeled CF betas. One caveat is that we study only cases in which the market portfolio return is used as the pricing kernel. By this we mean that we have not studied consumption-based or investment-based pricing kernels.[21] Our focus on the market portfolio is appropriate particularly because the return decomposition approach within this context has become an important tool that is widely used in many areas of research (see earlier references).

Our finding that value stocks do not have higher directly-modeled CF betas is consistent with Campbell, Polk, and Vuolteenaho (2005). When they use direct measures of the CF news for both the market portfolio and individual portfolios, they find that value portfolios tend to have lower CF betas in the post-1963 period, though in many cases the differences in the CF betas between the value and growth stocks are not significant (see Table 3 of their online appendix).

Our finding does not necessarily imply that the ICAPM representation in Campbell (1993) and Campbell and Vuolteenaho (2004) is invalid. The value premium puzzle is that value stocks earn higher returns than growth stocks even though the former have lower market betas. Campbell and Vuolteenaho (2004) argue that it is CF betas that matter and value stocks have higher CF betas. Our finding – value stocks might not have higher CF betas – suggests that the value premium puzzle remains. However, so long as the CF betas do not following the strong declining trend as the market betas do from growth to value stocks, the ICAPM interpretation helps to mitigate the value premium puzzle. In addition, the main purpose of this study is not to draw a conclusion on the trend of CF betas, but the difficulty of drawing such a conclusion using the return decomposition approach.

4.3 Variance decomposition

In Table 6 we examine the relative magnitude of the variances of the CF news and DR news for the market portfolio for the post-1963 period. The evidence is highly consistent with what we have obtained regarding the magnitude of the betas. We present nine different specifications. When the PE ratio is included in the VAR model, the variance of the DR news is much larger than the variance of the CF news. When the PE ratio is omitted, the variance of the CF news is usually larger than, or at least as large as, the variance of the DR news. For example, using the four state variables as in the benchmark case, we will conclude that about 79% of the variation of the expected market return is driven by the DR news and only 18% by the CF news, very close to Campbell and Ammer's results (1993). However, if we drop the PE ratio, we find the opposite: only 9% of the

[21] It has been found that, when (the low-frequency movement of) consumption news is used as the pricing kernel, value stocks can have higher CF betas (see Bansal, Dittmar, and Lundblad (2004) and Bansal, Dittmar and Kiku (2005)).

variation is driven by the DR news and 76% by the CF news. If we use the five state variables in Petkova (2004), we find that 38% of the variation of the unexpected market return is related to the DR news and 52% to the CF news, consistent with Kothari and Shanken (1992). While we report only the results for the post-1963 period, the relative magnitude of the variances of the DR news and CF news varies similarly for the pre-1963 period.

TABLE 6 ABOUT HERE

The relative weight of the DR news and CF news in driving equity returns at the aggregate level is important because it provides empirical guidance on the sources of systematic risks (see, for example, Campbell and Cochrane (1999) for a focused model of DR risk). We do not provide an answer here. Rather, the case in point is that the evidence provided through the variance decomposition approach might be sensitive to the state variables included.

4.4 Explanatory power of the cross-sectional regressions

We have shown that the CF beta patterns are sensitive to the state variables included. A natural question is whether we can decide which specification is the best. Because we usually judge the success of asset pricing models by their forecasting/explanatory power, we show in Table 7 the R-squares of the equity return forecasting equation in the VAR system and of the cross-sectional regressions for 11 different specifications.

TABLE 7 ABOUT HERE

As expected, the forecasting power for equity returns increases with the number of state variables. The interesting pattern lies in the R-squares of the cross-sectional regressions: they do not necessarily increase with the additional number of state variables. For example, when there are only two state variables, the excess return and the term spread, the R-square of the cross-section is 13%. When the PE ratio is added, the R-square plunges to 0%.

Why does the R-square of the cross-sectional regression not increase with the number of state variables? The return decomposition approach combines a chosen vector of factors into two components, during which process the influences of the state variables could cancel each other out, leading to reduced explanatory power. After all, we know the empirical patterns of equity returns: small value stocks earn higher returns. If the combined components cannot project into these directions, then the R-square must be small. Campbell and Vuolteenaho (2004) use the same intuition to argue that a separation of CF beta and DR beta can explain stock returns better than a single market beta because the signals in the separate betas can be muted in a single beta.

Given the large variation of the R-squares in the cross-sectional regression, one way to choose state variables is to regard the specification with the highest R-square as the "correct" one, which leads to the model in Panel B of Table 4. In fact, a general pattern in Table 7 is that, *ceteris paribus*, excluding the PE ratio always improves the cross-sectional R-square. This seems to suggest that we should exclude the PE ratio. However, our earlier results indicate that, once the PE ratio is excluded, we find patterns drastically different from those in the current literature regarding (i) the relative variances of the DR news and CF news, (ii) the magnitude of betas, and (iii) the cross-sectional patterns of the betas.

5 Further robustness check

5.1 Post-1952 data

When implementing the return decomposition approach, Campbell and Vuolteenaho (2004) 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 in all tables 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.

Table 8 about here

It turns out that this alternative procedure leads to dramatically different results. In Table 8 we use the same state variables as in the benchmark case, but use only the 1952:01-2001:12 period to decompose the market portfolio return.[22] Panel A shows a clear decreasing trend of the CF beta from the growth stocks to the value stocks. We also examine the sensitivity of this result to other choices of state variables as in the earlier tables and find the result to be surprisingly stable: In all the specifications we investigate, we find a declining trend of the CF beta from the growth stocks to the value stocks. Therefore, using a shorter sample period in the VAR system appears to yield a stable cross-sectional trend of the CF betas, but this trend is opposite to what has been documented in the current literature.

What happens to the variances of the DR news and CF news as well as the related betas? When only the post-1952 data are used for decomposition, we find that indeed, more likely than not, the DR variance is larger than the CF variance, and the magnitude of the DR betas is larger than that

[22] We use 1952 as the separating year to conform to the literature. Changing the separating year to 1963 does not change the results.

of the CF betas. But again there are exceptions: We do find combinations of state variables that reverse the above trends.

5.2 Other testable assets

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)). One way to test the robustness of the CF beta is to investigate whether it is priced in other testable assets. We use the 48 industry portfolios defined by Fama and French (1997).

Table 9 about here

The results for the industry portfolios are reported in Table 9. We use the same state variables as in the benchmark case. 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.

5.3 Other robustness checks

A large portion of this study is a robustness check for different model specifications. In addition, whenever space is allowed, we have reported the bootstrapping standard errors. As in Campbell and Vuolteenaho (2004), we provide further robustness checks in the following directions: (i) the magnitude of ρ, (ii) the conditional betas, and (iii) the data frequency. We find, without reporting, that changing ρ does not change the results. We have results (Panel C of Table 4 and all panels in Table 5) indicating that using quarterly or annual data does not alter the conclusions.

One concern is that the estimated betas might not be stable over time. As in Campbell and Vuolteenaho (2004), we adopt a 36-month rolling-window to estimate the conditional CF betas and DR betas for each portfolio. We use the same VAR specification as in Panel B of Table 4 because it has the highest cross-sectional R-square among all specifications. We report the average betas in Panel A of Table 10. They are very similar to those in Table 4. In Panel B of Table 10 we report the cross-sectional regressions for the 45 portfolios in Campbell and Vuolteenaho (2004) as well as the 48 industry portfolios. Even though the coefficient for the CF beta is positive, as we have argued before, this is not due to higher CF betas of value stocks. In addition, CF betas have a negative coefficient for the industry portfolio regression. While we report only the results for this particular specification, we find that, in general, estimating conditional betas does not change our earlier results.

TABLE 10 ABOUT HERE

6 Conclusions

The seminal work by Campbell and Shiller (1988a, 1988b) provides a method where unexpected equity returns can be decomposed into cash flow (CF) news and discount rate (DR) news. In many subsequent studies using this method, only the discount rate news is directly modeled, while the cash flow news is derived as the residual component. Some important conclusions are drawn, including (i) that the variance of the cash flow news is larger than that of the discount rate news for the market portfolio and the cash flow betas are usually higher than the discount rate betas for portfolios, consistent with the claim that the time-variation of the equity risk premium plays a central role; (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 cash flow news, as the residual, might reflect model noise instead of actual cash flow news. Any misspecification in modeling the discount rate might affect the relative magnitude of the cash flow news and the discount rate news, and subsequently any conclusion drawn based on their comparison.

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

We then examine equity returns. For many reasonable specifications, the cash flow variance is higher than the discount rate variance for the equity market portfolio, the cash flow betas are larger than the discount rate betas for portfolios, and value stocks usually do not have higher cash flow betas. These results run counter to those reported in the current literature using the same approach. We finally directly model the cash flow 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.

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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 (2004). 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: CAPM beta, cash flow beta, and discount rate beta

We use the same dataset as in Campbell and Vuolteenaho (2004). Panel A reports, for both the prewar and postwar 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 (2004) 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 (2004), 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 3: Betas with a subset or similar state variables

Campbell and Vuolteenaho (2004) 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 subsets of these variables in Panels A to B. In Panel C we replace the 10-year PE ratio with the dividend yield. In Panel D we replace the 10-year PE ratio with the 10-year PE ratio constructed by Shiller. 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 and value and growth firms are obtained through bootstrapping 2500 realizations. We then 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 reports only results during the period 1963:7 - 2001:12.

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

Panel A1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
Small	0.47		0.38		0.33		0.31		0.32		-0.15	[0.03]
2	0.41		0.33		0.29		0.25		0.26		-0.15	[0.03]
3	0.36		0.29		0.26		0.21		0.24		-0.12	[0.03]
4	0.33		0.27		0.23		0.20		0.22		-0.11	[0.03]
Large	0.23		0.22		0.18		0.16		0.17		-0.06	[0.02]
Diff	-0.24	[0.04]	-0.16	[0.03]	-0.15	[0.03]	-0.15	[0.03]	-0.15	[0.03]		

β_{DR}	Growth		2		3		4		Value		Diff	
Small	1.23		1.06		0.94		0.91		0.94		-0.29	[0.05]
2	1.15		0.97		0.89		0.82		0.89		-0.26	[0.05]
3	1.09		0.91		0.81		0.74		0.83		-0.26	[0.06]
4	0.97		0.86		0.77		0.70		0.78		-0.19	[0.05]
Large	0.80		0.74		0.64		0.59		0.63		-0.17	[0.06]
Diff	-0.43	[0.07]	-0.32	[0.07]	-0.30	[0.06]	-0.32	[0.06]	-0.31	[0.06]		

Panel A2: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	0.2774	0.8661	1.1435
Across 45 portfolios	0.2711	0.8548	1.1259

Panel B3: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	(0.47%)	-2.49%	0.95%	0.02%	-2.6309
S.E.	(0.21%)	(1.91%)	(0.81%)		

Table 3: Continued

Panel B: 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 B2: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	1.2851	-0.1321	1.1530
Across 45 portfolios	1.2563	-0.1220	1.1343

Panel C3: 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 3: Continued

Panel D: VAR variables include the excess equity market return, term spread, dividend yield, and value spread

Panel C1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
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]		

β_{DR}	Growth		2		3		4		Value		Diff	
Small	0.71		0.56		0.46		0.42		0.38		-0.33	[0.05]
2	0.65		0.46		0.37		0.31		0.32		-0.33	[0.04]
3	0.57		0.39		0.32		0.24		0.29		-0.28	[0.05]
4	0.52		0.37		0.29		0.25		0.26		-0.26	[0.04]
Large	0.41		0.30		0.24		0.18		0.19		-0.22	[0.04]
Diff	-0.30	[0.07]	-0.26	[0.06]	-0.22	[0.05]	-0.24	[0.05]	-0.19	[0.05]		

Panel C2: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	0.7633	0.3785	1.1418
Across 45 portfolios	0.7443	0.3796	1.1238

Panel D3: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	-0.01%	1.85%	-2.02%	50.22%	-0.9185
S.E.	(0.14%)	(0.30%)	(0.30%)		

Table 3: Continued

Panel E: VAR variables include the excess equity market return, term spread, value spread, and the Shiller 10-year PE ratio

Panel D1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
Small	0.34		0.27		0.24		0.23		0.25		-0.09	[0.05]
2	0.29		0.24		0.22		0.19		0.21		-0.08	[0.05]
3	0.25		0.22		0.20		0.17		0.19		-0.06	[0.05]
4	0.23		0.21		0.19		0.16		0.18		-0.05	[0.04]
Large	0.16		0.16		0.15		0.14		0.14		-0.02	[0.05]
Diff	-0.18	[0.08]	-0.11	[0.07]	-0.09	[0.06]	-0.09	[0.06]	-0.11	[0.06]		

β_{DR}	Growth		2		3		4		Value		Diff	
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]		

Panel D2: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	0.2086	0.9201	1.0438
Across 45 portfolios	0.2021	0.9092	1.0461

Panel E3: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	-0.76%	4.48%	-1.16%	11.63%	-3.8621
S.E.	(0.13%)	(2.02%)**	(0.50%)**		

Table 4: Betas with additional state variables

We use additional state variables in the VAR system following the literature. As in Table 3, 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 firms and value and growth firms are obtained through bootstrapping 2500 realizations. We then 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. In Panel C we add variables shown by Ludvigson and Ng (2005) to exhibit good predictive power for equity returns. Because these variables are available only at quarterly frequency, Panel C reports results at quarterly interval while Panels A and B report results at monthly frequency. We present results only for the 1963-2001 period.

Panel A: VAR variables: excess equity market return, term yield, dividend yield, credit spread, and risk-free rate (Petkova (2004))

Panel A1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
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]		

β_{DR}	Growth		2		3		4		Value		Diff	
Small	0.24		0.17		0.11		0.09		0.09		-0.15	[0.06]
2	0.20		0.09		0.06		0.01		0.05		-0.15	[0.06]
3	0.13		0.07		0.03		0.00		0.04		-0.09	[0.06]
4	0.10		0.08		0.02		-0.02		0.00		-0.10	[0.06]
Large	0.12		0.07		0.07		0.02		0.04		-0.08	[0.05]
Diff	-0.12	[0.07]	-0.10	[0.06]	-0.04	[0.07]	-0.07	[0.05]	-0.05	[0.05]		

Panel A2: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	1.0828	0.0756	1.1584
Across 45 portfolios	1.0588	0.0811	1.1400

Panel A3: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	0.16%	0.66%	-3.20%	35.29%	-0.2072
S.E.	(0.15%0	(0.17%)	(0.63%)		

Table 4: Continued

Panel B: VAR variables: excess equity market return, term spread, value spread, credit spread, dividend yield, book-to-market spread, and market-to-book spread

Panel B1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
Small	0.97		0.88		0.81		0.81		0.90		-0.07	[0.07]
2	0.90		0.79		0.74		0.71		0.79		-0.11	[0.07]
3	0.82		0.73		0.68		0.65		0.74		-0.08	[0.07]
4	0.73		0.70		0.64		0.59		0.68		-0.05	[0.07]
Large	0.51		0.55		0.50		0.49		0.55		0.04	[0.07]
Diff	-0.46	[0.10]	-0.33	[0.09]	-0.31	[0.08]	-0.32	[0.08]	-0.35	[0.07]		

β_{DR}	Growth		2		3		4		Value		Diff	
Small	0.70		0.54		0.44		0.40		0.34		-0.36	[0.08]
2	0.64		0.49		0.42		0.35		0.35		-0.29	[0.07]
3	0.60		0.45		0.37		0.29		0.33		-0.27	[0.08]
4	0.56		0.43		0.35		0.31		0.31		-0.25	[0.08]
Large	0.51		0.40		0.32		0.26		0.25		-0.26	[0.07]
Diff	-0.19	[0.11]	-0.14	[0.10]	-0.12	[0.08]	-0.14	[0.08]	-0.09	[0.08]		

Panel B2: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	0.7147	0.4163	1.1311
Across 45 portfolios	0.6809	0.4324	1.1134

Panel B3: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	0.55%	1.30%	-1.92%	71.81%	-0.6752
S.E.	(0.07%)	(0.14%)	(0.18%)		

Table 4 − Continued

Panel C: VAR variables: excess equity market return, term spread, PE ratio, value spread, cay, risk-premium factor, and volatility factor

Panel C1: Betas

β_{CF}	Growth		2		3		4		Value		Diff	
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]		
β_{DR}												
Small	1.06		0.91		0.78		0.76		0.78		-0.32	[0.14]
2	0.87		0.66		0.69		0.60		0.63		-0.24	[0.14]
3	0.79		0.67		0.60		0.54		0.55		-0.24	[0.14]
4	0.74		0.55		0.53		0.51		0.55		-0.19	[0.14]
Large	0.65		0.48		0.38		0.41		0.48		-0.17	[0.13]
Diff	-0.51	[0.18]	-0.43	[0.16]	-0.40	[0.14]	-0.35	[0.13]	-0.30	[0.12]		

Panel B2: Cross-sectional regressions

	Intercept	β_{CF}	β_{DR}	Adjusted R^2	γ
Across 45 portfolios					
Coefficient Estimate	0.83%	11.11%	-4.11%	50.39%	-2.7013
Standard Error	(0.31%)	(1.71%)	(0.72%)		
Across 48 industry portfolios					
Coefficient Estimate	1.69%	-0.46%	1.34%	6.29%	-0.3468
Standard Error	(0.53%)	(1.74%)	(0.79%)		

Table 5: 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 cases for dividend growth rate; Panel B report the cases 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 5 − 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 6: Variances of cash flow news and discount rate news

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 particular model. This table reports only results during the period 1963:7 - 2001:12.

	Models								
	1	2	3	4	5	6	7	8	9
Excess return	+	+	+	+	+	+	+	+	+
Term spread	+	+	+	+			+	+	+
PE ratio		+		+					+
Value spread			+	+				+	+
Credit spread					+	+	+	+	+
Dividend yield						+	+	+	+
Book-to-market spread								+	+
Market-to-book spread								+	+
Risk free rate							+		
Variance of CF	0.41%	0.05%	0.44%	0.06%	0.30%	0.20%	0.22%	0.19%	0.08%
Variance of DR	0.03%	0.22%	0.05%	0.27%	0.01%	0.06%	0.15%	0.17%	0.29%
Cov(CF, DR)	0.07%	-0.02%	0.09%	0.01%	0.00%	-0.03%	0.03%	0.03%	0.03%

Table 7: Explanatory power of the cross-sectional regressions

We report the adjusted R-squares of the equity prediction functions and of the cross-sectional regressions of the average returns for the 45 portfolios in Campbell and Vuolteenaho (2004). These R-squares vary when different state variables are included but do not necessarily increase at all when more stable variables are considered. This table reports only results during the period 1963:7 - 2001:12.

	Models										
	1	2	3	4	5	6	7	8	9	10	11
Excess return	+	+	+	+	+	+	+	+	+	+	+
Term spread	+	+	+	+	+	+	+	+	+	+	+
PE ratio		+		+	+		+		+	+	
Value spread			+	+	+	+	+	+		+	
Credit spread					+	+	+	+	+	+	+
Div. yield						+	+	+	+	+	+
BM spread								+	+	+	
MB spread								+	+	+	
Riskfree rate											+
adjusted R^2 of the return prediction equation in VAR (%)											
	1.46	2.02	1.74	2.57	2.57	2.27	2.60	2.96	2.24	3.03	1.80
adjusted R^2 of the cross-section (%)											
Before 1963:6	44.83	43.60	47.37	44.76	42.86	43.63	42.89	42.79	42.95	42.51	42.69
After 1963:7	12.85	0.02	52.36	49.99	46.57	48.97	36.41	71.81	50.68	62.42	35.29

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

In Campbell and Vuolteenaho (2004), 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 (2004). We first 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. We then 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 reports only cash flow and discount rate betas during the 1963:7 - 2001:12 period.

Panel A: Cash flow and discount rate betas

Panel A1: Betas

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]		

Panel B: Average betas

	Cash Flow beta	Discount Rate beta	Market beta
Across 25 FF portfolios	0.4271	0.7296	1.1516
Across 45 portfolios	0.4183	0.7191	1.1374

Panel C: Cross-sectional regression

	Intercept	β_{CF}	β_{DR}	Adj. R^2	γ
Coeff.	0.64%	6.64%	3.90%	15.80%	-1.6893
S.E.	(0.12%)	(2.14%)	(1.23%)		

Table 9: Is cash flow beta priced in industry portfolios ?

Using the same state variables as in Campbell and Vuolteenaho (2004), 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 10: Conditional beta

We adopt a 36-month rolling-window to calculate betas. We include the following state variables in the VAR system: the excess market return, the term spread, the value spread, the credit spread, the dividend yield, the book-to-market spread, and the market-to-book spread. As in Table 4, we use this VAR system because it provides the highest cross-sectional R-squares. In Panel A we report the average rolling-betas. In Panel B we report the average coefficients in the cross-sectional regressions for the 45 portfolios in Campbell and Vuolteenaho (2004) and 48 industry portfolios. This table reports only results during the period 1963:7 - 2001:12.

Panel A: Average betas

β_{CF}	Growth		2		3		4		Value		Diff	
Small	1.00		0.90		0.84		0.83		0.95		-0.05	[0.01]
2	0.91		0.81		0.75		0.73		0.83		-0.08	[0.01]
3	0.83		0.73		0.69		0.69		0.77		-0.06	[0.01]
4	0.71		0.70		0.66		0.62		0.72		0.01	[0.01]
Large	0.51		0.55		0.51		0.51		0.59		0.08	[0.01]
Diff	-0.49	[0.02]	-0.35	[0.02]	-0.33	[0.02]	-0.32	[0.02]	-0.36	[0.02]		
β_{DR}												
Small	0.66		0.55		0.46		0.42		0.35		-0.31	[0.01]
2	0.66		0.52		0.46		0.40		0.39		-0.27	[0.01]
3	0.62		0.48		0.41		0.34		0.35		-0.27	[0.01]
4	0.55		0.43		0.38		0.34		0.36		-0.19	[0.01]
Large	0.50		0.40		0.30		0.28		0.28		-0.22	[0.01]
Diff	-0.16	[0.02]	-0.15	[0.02]	-0.16	[0.02]	-0.14	[0.02]	-0.07	[0.02]		

Panel B: Average coefficients of cross-sectional regressions

	Intercept	β_{CF}	β_{DR}	Adjusted R^2	γ
Across 45 portfolios					
Coefficient Estimate	1.18%	(0.23%)	-0.62%	40.50%	-0.5659
Standard Error	(0.05%)	(0.06%)	(0.08%)		
Across 48 industry portfolios					
Coefficient Estimate	0.68%	-0.62%	-0.05%	17.00%	0.1514
Standard Error	(0.04%)	(0.14%)	(0.05%)		

Table A1: Variance and beta decomposition of Treasury bond 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 nominal 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 (2004). We then report the variances of the two components and their covariances. The state variables include different combinations of the term spread, expected real interest rate, expected inflation, and the credit spread. The plus signs in Panel A indicate the selected variables in each scenario. Expected real interest rate and expected inflation are estimated following Fama and Gibbons (1982). 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 60-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 60-month bond return as the market portfolio and calculate the betas for portfolios with maturity ranging from 6 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 standard errors obtained from bootstrapping 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)
	+			2.4416	0.1878	0.4941
+				2.4672	0.1403	0.4830
+	+			2.4757	0.2461	0.5410
	+	+		4.6804	2.1184	2.6053
+	+	+		6.0907	3.6842	4.0943
	+	+	+	4.2248	2.0516	2.3476
+	+	+	+	4.9397	2.8941	3.1263

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)	-0.0088	0.0582	0.3174	-0.2403	-0.0582	0.1021
Intermediate-term bonds (2)	1.2351	-0.0388	1.3691	-0.2496	1.2175	-0.0095
Long-term bonds (3)	1.8879	-0.0584	1.9093	-0.3121	1.8890	-0.0223
(3) - (1)	1.8966	-0.1166	1.5920	-0.0718	1.9472	-0.1244
Standard deviation of (3) - (1)	(0.2247)	(0.2684)	(0.2347)	(0.2075)	(0.2581)	(0.3088)

Table A1 – 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	-1.5509	-	-	0.2657	-	-
2-year	-1.1814	0.3695	(0.0330)	0.2034	-0.0623	(0.0065)
3-year	-0.9038	0.2776	(0.0319)	0.1542	-0.0491	(0.0091)
4-year	-0.6185	0.2853	(0.0502)	0.0995	-0.0548	(0.0129)
5-year	-0.3689	0.2496	(0.0411)	0.0574	-0.0421	(0.0133)
Panel C2: Fama bond portfolios						
Maturity	β_{CF}	Diff.	S.E. of diff	β_{DR}	Diff.	S.E. of diff
Less than 6 months.	-1.8706	-	-	0.3148		-
Less than 12 months	-1.6732	0.1974	(0.0193)	0.2832	-0.0316	(0.0042)
Less than 18 months	-1.4916	0.1816	(0.0147)	0.2522	-0.0310	(0.0043)
Less than 24 months	-1.3323	0.1593	(0.0155)	0.2267	-0.0255	(0.0044)
Less than 30 months	-1.1760	0.1563	(0.0175)	0.2005	-0.0262	(0.0050)
Less than 36 months	-1.0688	0.1072	(0.0224)	0.1834	-0.0170	(0.0077)
Less than 42 months	-1.9684	0.1005	(0.0300)	0.1612	-0.0222	(0.0108)
Less than 48 months	-1.8740	0.0944	(0.0209)	0.1458	-0.0155	(0.0081)
Less than 54 months	-0.8085	0.0654	(0.0260)	0.0.1343	-0.0115	(0.0094)
Less than 120 months	-0.4564	0.3522	(0.0429)	0.0671	-0.0672	(0.0136)

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%.