Return Decomposition

Long Chen
Washington University in St. Louis

Xinlei Zhao
Kent State University

A crucial issue in asset pricing is to understand the relative importance of discount rate (DR) news and cash flow (CF) news in driving the time-series and cross-sectional variations of stock returns. Many studies directly estimate the DR news but back out the CF news as the residual. We argue that this approach has a serious limitation because the DR news cannot be accurately measured due to the small predictive power, and the CF news, as the residual, inherits the large misspecification error of the DR news. We apply this residual-based decomposition approach to Treasury bonds and equities and find results that are either counterintuitive or unrobust. Potential solutions, including modeling both DR news and CF news directly, the Bayesian model averaging approach, and the principal component analysis, are explored. (*JEL* G11, G12)

The seminal work by Campbell and Shiller (1988a) suggests that unexpected asset returns can be decomposed into two components: news about discount rates (DRs) and news about cash flows (CFs). Naturally, financial economists place keen interest in the relative importance of CF news and DR news—the two fundamental components of asset valuation—in determining the time-series and cross-sectional variations of stock returns. Relatively speaking, CF news is more related to firm fundamentals because of its link to production; DR news can reflect time-varying risk aversion or investor sentiment. Their relative

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importance thus helps greatly to understand how the financial market works, and provides the empirical basis for theoretical modeling.[1]

One popular approach in the study of the DR news and CF news is to directly model the DR news and back out the CF news as the residual. As Campbell and Vuolteenaho (2004a, p. 1253) 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 method the *return decomposition approach* in the rest of the paper.

This easy-to-implement approach has led to a voluminous literature across many disciplines, including finance, accounting, and macroeconomics; some important conclusions have been drawn regarding the relative role of CF/DR news and cited widely by academicians, practitioners, and policy makers (see literature review below). Despite the rapid expansion and important implications, little effort has been spent examining the validity and robustness of this approach. We make the first attempt to fill in this void.

We argue that the return decomposition approach has a serious limitation: the CF news could very well be a catchall for modeling noise. The DR news usually cannot be accurately measured due to the well-known small predictive power; the CF news, as the residual, inevitably inherits the large misspecification error of the DR news. 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 magnitude of the variances and cause cross-sectional biases if the missing state variable is priced cross-sectionally in asset returns. We provide a simple theoretical example to show that omitting state variables can lead to misleading cross-sectional beta patterns.

While model misspecification is always a potential problem any empirical 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 inferences about the specified factors despite increased noise, so long as the omitted factor is not highly 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 CFs of these securities are fixed: real interest rate 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 there is no nominal CF uncertainty; the estimated "CF news" contains no actual

[1] For example, to explain the equity premium puzzle, Campbell and Cochrane (1999) focus on modeling the DR risk, while Bansal and Yaron (2004) model both DR risk and CF risk.

CF news but is pure modeling noise.[2] Treasury bonds thus provide a unique opportunity to separate true CF 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 along the maturity dimension.

In stark contrast, we find that the estimated variance of the "CF news" is larger than, or at least as large as, 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. Because we know the so-called CF news is in fact DR news in disguise, the evidence suggests that missing state variables in the DR forecast can induce misleading patterns and cause us to draw wrong conclusions regarding (i) the relative variances, (ii) the relative magnitude of betas, and (iii) the cross-sectional patterns of betas.

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

In contrast, we find that the benchmark case is sensitive to close substitutes and to sample periods. In particular, as Campbell and Vuolteenaho (2004a) point out, the impact of a state variable is a function of its persistence. The dominant variable in the benchmark case is the 10-year smoothed PE ratio with an autocorrelation of more than 0.99, which raises serious stationarity concerns. Because the PE ratio is meant to capture expected returns, we replace the 10-year PE ratio by close substitutes that perform similar roles, including (i) the 1-year PE ratio, which is less smoothed; (ii) the dividend yield, which is more commonly used to predict equity returns;[3] (iii) the book-to-market ratio (e.g., Kothari and Shanken 1997; Pontiff and Schall 1998; Lewellen 1999); and

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[2] Note in all previous studies in this literature, the CF news is always nominal. For equities, inflation risk can be classified as both DR risk and CF risk because both the nominal DR and expected future CF can increase with inflation. For Treasury bonds, however, inflation shocks can only affect the DR. Accordingly, nominal interest rate reflects expected inflation but bond nominal CFs are fixed. See Campbell and Vuolteenaho (2004b), who use this difference between equity and bond to study inflation illusion.

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

(iv) the book-to-market spread (Liu and Zhang 2008), the inclusion of which makes the (dropped) 10-year PE ratio insignificant but other variables more significant, and thus improves the overall explanatory power. In all these cases, we find that value stocks have lower CF betas, contrary to the finding in the benchmark case.[4] That is, seemingly innocuous modifications of the model lead to opposite conclusions. We further explore the variables in Goyal and Welch (2008), who have perhaps the most recent comprehensive list of variables that predict equity returns. It is fair to say that, for most combinations, value stocks do not have higher CF betas.

The relative importance of the DR news and the CF news of the market portfolio varies in a fashion similar to the cross-sectional pattern of the betas, depending on the state variables that are included. For example, with monthly data, the benchmark case leads to the conclusion that the DR variance far exceeds the CF variance for the 1929–2001 period. However, this pattern flips back and forth when we replace the 10-year PE ratio by other scaled-price variables: replacing it by the dividend yield leads to the finding that CF variance is slightly higher; replacing it by either the 1-year PE ratio or the book-to-market ratio leads to the finding that the CF variance is either similar to or higher than the DR variance for the post-1952 period; replacing by the book-to-market spread, even though it improves the predictive power of equity return, leads to the finding that the CF variance dominates for all periods.

Why are the results using the return decomposition approach so sensitive to the choice of state variables? Theoretically, this approach works perfectly if one knows the true model; empirically, the DR news is calculated by amplifying the predictive coefficients (usually estimated with noise) into the infinite horizon through the high persistence of state variables. This high persistence explains why Campbell and Ammer (1993) and Campbell and Vuolteenaho (2004a) can find that DR news dominates the CF news even though the return predictability is small. It also explains why minor modifications of the state variables can completely change the conclusions regarding the relative importance of CF/DR news in driving the time series and cross-section of stock returns. It is so because one does not know the true model. Different specifications change the level of persistence and the predictive coefficients. As a result, the DR news has changed; and the CF news, as the residual, has also changed.

Model sensitivity is inevitable in empirical work. For most empirical work, though, it usually affects only the statistical significance of the estimators. The essence of the residual-based return decomposition approach, however, is to compare the modeled part with the residual; the conclusions are usually a choice between "more important" and "less important" or between "higher" and "lower." Since model misspecification often leads to opposite conclusions, this sensitivity is not a robustness issue; it is a vital issue. A key contribution

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

of our paper is to explain why this approach could be sensitive, and show that it is indeed so.

Nevertheless, the concept of return decomposition, as proposed by Campbell and Shiller (1988a), is elegant and has profound implications. The question is what can be learned from our findings and what can be done to proceed. We have the following suggestions.

First, while it is important to choose predictive variables well motivated by economic reasons, it is far from enough. The reason is that most predictive variables are related to the macroeconomy and thus are all "well motivated." Our finding, that minor changes of the predictive models can lead to opposite conclusions, suggests that an extensive model search is needed if one wants to place confidence in his findings. Conclusions drawn from this approach and future references on these conclusions should be taken with caution because they are based on a specific model.[5]

Second, a natural improvement of the residual-based decomposition approach is to model both the CF news and the DR news. Such a procedure effectively separates the CF news in the current decomposition approach into modeled CF news and residual news. It acknowledges that the nature of the residual news is unknown but the modeled CF news and DR news can be compared on equal footing. We conduct such an exercise in the paper. Given that dividends might be subject to corporate policies, we use two separate CF measures, dividend growth rate and earnings return on equity, to calculate CF betas. They lead to the same inference: in the benchmark case, value stocks have both lower CF betas and lower DR betas, but higher residual betas. In other words, the results in the current literature are driven by the residual betas. Depending on whether the residual news represents CF news or DR news, opposite conclusions can be drawn, which further points to the danger of drawing conclusions based on the residual-based approach.[6]

Third, to address the problem of model uncertainty, one can apply the Bayesian model averaging approach (Avramov 2002; Cremers 2002) to a large

[5] We emphasize that studies in the return decomposition literature usually conduct extensive robustness checks. Presumably because they choose state variables based on their priors, only limited attention has been given to the sensitivity of these choices. For example, Campbell and Vuolteenaho (2004a) provide robustness checks for many aspects of their model. They also show that the results in the benchmark case continue to hold in several alternative specifications (reported in their online appendix). Our findings suggest that model sensitivity is of first-order importance and extensive robustness checks should be done in this regard before any conclusion is drawn.

[6] In response to our critique, Campbell, Polk, and Vuolteenaho (2009) made the following statement: "Chen and Zhao (2008) claim that the results of this methodology are sensitive to the decision to forecast expected returns explicitly and treat cash flows as a residual. This claim is incorrect. The important decision in implementing this methodology is not the decision to forecast returns or cash flows, but the choice of variables to include in the VAR." Their statement is a misinterpretation of our conclusion. We have made it clear that, due to small predictive power, the DR news cannot be accurately measured, and the CF news, as the residual, inevitably inherits the large misspecification error of the DR news. For this reason, the choice of predictive variables is important because whatever is missing is likely to affect the relative importance of DR news and CF news. Therefore, the methodology of predicting returns explicitly and treating cash flows as the residual has a serious limitation. One way to get around this problem is to predict both returns and CFs directly.

set of predictive variables. The idea is to examine all combinations of the predictive variables, assign higher posterior weights to models that predict returns better, and draw conclusions based on such weights. Alternatively, since one does not know the true model, one can also recover the principal components from a large set of predictive variables and use these principal components as the state variables. We investigate both approaches. The results still vary depending on the pool of predictive variables. In general, the conclusion that value stocks have higher CF betas seems to hold only under some special specifications but does not hold for most other specifications.[7] On the other hand, it seems difficult to draw a clear-cut conclusion regarding the relative importance of CF/DR variances for the market portfolio since the evidence flips frequently depending on the model specifications.

The rest of the paper proceeds as follows: Section 1 provides theoretical discussions. Sections 2 and 3 examine Treasury bond returns and equity returns, respectively, based on the return decomposition approach. Section 4 searches for potential remedies that can improve upon the return decomposition approach. Section 5 conducts further robustness checks, and Section 6 concludes.

1. Theoretical Discussion

1.1 Decomposition procedure

The idea that unexpected stock returns can be approximated by a linear combination of cash flow (CF) news and discount rate (DR) news dates back to Campbell and Shiller (1988a). Campbell (1991) further provides the following decomposition of the unexpected return:

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

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

[7] There is a growing literature that studies the importance of CF risk (e.g., Bansal and Yaron 2004; Bansal, Dittmar, and Lundblad 2005; Lettau and Wachter 2005; Kiku 2006; Santos and Veronesi 2006; Cohen, Polk, and Vuolteenaho 2008; Da 2008; and Hansen, Heaton, and Li 2008). We differ from this literature in that we directly estimate the CF news and DR news contained in return, while this literature usually directly studies CF measures (not necessarily in returns). As such, the focus and the conclusions could be different.

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

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

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

$$\beta_i = \frac{Cov(e_i, e_{CF})}{Var(e)} + \frac{Cov(e_i, -e_{DR})}{Var(e)} \tag{3}$$

$$= \beta_{i,CF} + \beta_{i,DR}, \tag{4}$$

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

In the empirical implementation, Campbell and Vuolteenaho (2004a) assume that a vector of state variables, z_{t+1}, evolves according to a first-order vector autoregression (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 DR news is

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

where $\lambda = \rho\Gamma\,(I - \rho\Gamma)^{-1}$, 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 CF news can then be backed out as the difference between the total unexpected return and the DR news,

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

It follows that

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

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

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

Following Campbell and Vuolteenaho (2004a), two adjustments are made in actual calculation. First, we use excess returns in the VAR 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; Dimson 1979).

1.2 An ICAPM interpretation

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

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

where $r_{i,t+1}$ is the return for asset i, $r_{f,t+1}$ is the risk-free 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 greater than 1 (e.g., γ is between 7.5 and 10 in Bansal and Yaron 2004). For this reason, Campbell and Vuolteenaho (2004a) call the CF beta the "bad beta" and the DR beta the "good beta." The intuition is that a higher unexpected market equity return, if DR related, implies lower future growth opportunities (i.e., lower returns). If a stock has a positive DR beta, meaning that the stock pays more when the market's expected future growth opportunity shrinks, it is welcomed by conservative investors and thus is less penalized.

1.3 Implications

We can integrate the VAR system into Equation (10) to obtain

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

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 the factor matters.[8] The approach does differ from a regular multifactor model in the sense

[8] That is, the approach is subject to the "fishing license" critique made by Fama (1991).

that, no matter how many state variables are chosen, they must be combined into two components (i.e., the CF beta and the DR beta).

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

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 the case in Campbell and Vuolteenaho (2004a) because equity return has a positive autocorrelation. 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 will induce different cross-sectional patterns in the DR betas, if the factors have different cross-sectional effects on stocks. The CF betas are also affected because they are backed out from the DR betas. Similarly, it can be shown that omitting a state variable can also 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 inferences on the specified factors, if the omitted factors are not highly correlated with the specified ones. In the decomposition approach, however, the omission of state variables will directly affect both the DR news and the CF news, and the relative balance between them.

1.3.1 Current literature. This discussion has direct implication for the current literature. In the early 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.[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 (2004a), Koubouros, Malliaropulos, and Panopoulou (2004), and Campbell, Polk, and Vuolteenaho (2009) estimate the CF betas; Hecht and Vuolteenaho (2006) use residual-based CF proxies to study whether the relation between equity return and CF proxies represents CF news; Campbell and Vuolteenaho (2004b) use residual-based CF proxies to study how inflation illusion explains asset misvaluation; in the macroeconomics literature, Patelis (1997) and Bernanke and Kuttner (2005) study how unexpected monetary policy changes can affect stock returns through DR news and CF news; in the accounting literature, Callen and Segal (2004), Callen, Hope, and Segal (2005), Callen, Livnat, and Segal (2006), and Sadka (2007) model DR news and back out either accrual news, foreign earnings news, or earnings news as the residual component and study its importance, and Khan (2008) uses the residual-based CF news as a risk factor to explain the accrual anomaly. This easy-to-implement approach has thus led to an influential literature that covers many disciplines and delivers important messages to academicians, practitioners, and policy makers.

[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.

This study only concerns the corresponding parts of these studies—they also explore many interesting questions 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 the choice of state variables. Nevertheless, many 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 little addressed, however, is to what extent the conclusions are sensitive to alternative model specifications.

The answer to this question is important. Empiricists (like us) are taught to tolerate some degree of model misspecification because it is difficult to find the "true model." The essence of the residual-based return decomposition approach, however, is to compare the modeled part with the residual; the conclusions are usually a choice between "more important" and "less important" or between "higher" and "lower." Since model misspecification can lead to opposite conclusions, this sensitivity is not a robustness issue; it is a vital issue.

We emphasize that the problems discussed here are all empirical. Theoretically, the return decomposition approach works perfectly if we know the "true model" to predict returns; empirically, most state variables have low predictive power, meaning that the DR news (and subsequently CF news) is estimated with large misspecification errors and is likely to be sensitive to the choice of state variables. The gist of this study is to examine the sensitivity of previously drawn conclusions when the information set of predictive variables varies.

2. 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 both the true CF news and noise due to our limited ability to predict DR. For Treasury bonds, however, the nominal CFs are fixed. Any real interest rate 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 DRs, not nominal bond CFs. If we apply the return decomposition, the estimated "CF news" must be purely modeling noise. Therefore, Treasury bonds provide a unique opportunity to examine what happens if we have limited ability to predict DR.

We use a similar log-linear approximation as before:

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

[10] For example, in both Campbell and Ammer (1993) and Campbell and Mei (1993), the real interest rate news is directly considered and its importance relative to other modeled factors is studied.

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

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

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

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

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

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

where $\lambda_2 = (\Gamma - \Gamma^N)(I - \Gamma)^{-1}$.[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 know the actual CF variance must be zero. Therefore, if the model is properly specified, the DR variance should far exceed the CF variance. In addition, the CF betas are expected to be close to zero and thus there should be no cross-sectional dispersion of the CF betas. Furthermore, bond portfolios with longer maturity are expected to have higher DR betas because of the discounting effect on more remote CFs (see Campbell and Vuolteenaho 2004a for a similar argument for equities with more remote cash flows, i.e., growth stocks).

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 real interest rate, inflation, and the credit spread (Baa over Aaa yield).[12,13]

Results on Treasury bond returns are shown in Table 1. In Panel A, we use the Ibbotson dataset covering the 1926–2002 period. We use the intermediate-term bond return in excess of the 3-month Treasury-bill rate as the excess return of

[11] Campbell and Ammer (1993) point out that there might be some modeling noise because of the change of bond maturity from one month to the next. Such noise is unlikely to be the main driver of the results.

[12] 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).

[13] We adopt this procedure to be consistent with some recent studies in predicting bond returns (Baker, Greenwood, and Wurgler 2003). Alternatively, we can use nominal interest rate (instead of real interest rate and inflation) as the state variable. The results are similar and are available upon request.

Table 1
Variance and beta decomposition of Treasury bond excess returns

Panel A: Variance decomposition

Variables in VAR				Variances (%)		
Term spread	Real rate	Inflation	Credit spread	Var (*CF*)	Var (*DR*)	Cov (*CF*, *DR*)
	+			0.33	0.17	0.09
+				0.53	0.08	0.14
+	+			0.42	0.18	0.16
	+	+		0.18	0.18	0.03
+	+	+		0.21	0.16	0.06
	+	+	+	0.17	0.16	0.02
+	+	+	+	0.19	0.13	0.03

Panel B: Beta decomposition using Ibbotson data

	Full sample			
	β_{CF}	β_{DR}	$\beta_{CF}-\beta_{DR}$	S.E.
30-day T-Bill (1)	0.14	0.02	0.12	(0.06)
Long-term bond (2)	1.02	0.51	0.51	(0.46)
(2) – (1)	0.88	0.49		
S.E. of (2) – (1)	(0.27)	(0.26)		

Maturity	β_{CF}	Diff.	S.E. of Diff	β_{DR}	Diff.	S.E. of Diff	$\beta_{CF}-\beta_{DR}$	S.E.
Panel C1: Fama-Bliss zero coupon bonds								
2-year	0.18			0.11			0.07	(0.12)
3-year	0.31	0.13	(0.06)	0.24	0.12	(0.06)	0.08	(0.23)
4-year	0.42	0.11	(0.05)	0.31	0.08	(0.05)	0.11	(0.31)
5-year	0.52	0.10	(0.05)	0.38	0.07	(0.05)	0.14	(0.38)
Panel C2: Fama bond portfolios								
1-year	0.25			0.10			0.15	(0.14)
2-year	0.40	0.14	(0.06)	0.21	0.11	(0.04)	0.19	(0.19)
3-year	0.53	0.13	(0.05)	0.32	0.10	(0.05)	0.21	(0.25)
4-year	0.61	0.08	(0.05)	0.39	0.08	(0.05)	0.21	(0.29)
5-year	0.71	0.10	(0.08)	0.36	−0.03	(0.07)	0.35	(0.33)
10-year	0.73	0.02	(0.07)	0.45	0.09	(0.07)	0.28	(0.36)

We apply the return decomposition approach to Treasury bond returns using annual data (aggregated from monthly data) covering 1953–2002. In Panel A, we decompose the excess return of intermediate-term Treasury bond into discount rate (DR) news and cash flow (CF) news. We then report the variances of the two components and their covariance. The state variables include different combinations of the term spread (the difference between the long-term and short-term bond yields), real interest rate, inflation, and credit spread (Baa over Aaa bond yield). The plus signs indicate the selected variables in each scenario. In Panel B, we use the intermediate-term Treasury bond (from Panel A) as our bond market portfolio and calculate the discount rate beta and cash flow beta for 30-day T-bill and long-term bond. Similarly, in Panel C1, we calculate the betas for Fama-Bliss zero coupon bonds ranging from two to five years. In Panel C2, we calculate the betas for the Fama bond portfolios ranging from one year to 10 years. In Panels B and C, the "Diff" columns report the differences in betas of two adjacent portfolios with different maturities; the "$\beta_{CF}-\beta_{DR}$" columns report the differences in cash flow and discount rate betas of the same portfolio. In Panels B and C, we report bootstrap standard errors (S.E.) from 10,000 simulated realizations.

the bond market portfolio.[14] The original data is at monthly frequency but we aggregate them into annual frequency because we find that bond returns are much more predictable at such a frequency.

In Panel A of Table 1, we report different combinations of the four state variables. The R-squared of the excess return equation ranges from 16% to 35%,

[14] 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.

with the R-squared being the highest when all four variables are included.[15] The CF news variance is larger than or at least as large as the DR news variance in all cases.[16] This "CF news" is in fact the DR news that is not picked up by our VAR model specification. The finding that the CF variance, which is supposed to be zero, is never smaller than 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 of Table 1, we calculate the CF betas and DR betas for the 30-day T-bill and the long-term bond, using the same bond market portfolio as in Panel A. Two patterns emerge. 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 maturities are expected to have higher DR betas but zero CF betas. In stark contrast, we find that both the DR and CF betas increase with maturity, and the increase of the CF beta (0.88) is much larger than the increase of the DR beta (0.49).

Throughout the paper, standard errors of the betas are obtained via bootstrapping following Campbell and Vuolteenaho (2004a). We use bootstrapping because the betas are defined differently from the CAPM betas (see Equation (3)). In each simulation, variables in the VAR system (including excess return) are generated using the VAR coefficients estimated from the original data; that is, they are simulated under the assumption that the VAR variables are predictable. We then re-estimate the VAR coefficients for each simulation and estimate betas based on these re-estimated VAR coefficients. The standard errors of the betas are based on 10,000 simulations.[17]

The patterns in Panel B of Table 1 are further confirmed in Panel C. In particular, Panel C1 uses the annual return data of Fama-Bliss (1987) zero-coupon bonds covering the 1952–2003 period. There are bond prices for five maturities, from one to five years, which means that returns of four portfolios can be formed.[18] Panel C2 reports betas for the so-called Fama maturity bond portfolios, obtained from CRSP, covering the 1952–2003 period. The maturities range from one to ten years. We use the same market portfolio as in Panel A and calculate the betas for all the portfolios in Panel C.

[15] While untabulated, we find that the signs and significance of the state variables are very close to those in Baker, Greenwood, and Wurgler (2003).

[16] Note that the impact of DR news and CF news show up not only in their variances, but also in their covariance. Here we only compare the variances.

[17] We have tried alternative bootstrapping methods, including the simple block bootstrapping and the stationary block bootstrapping (Politis and Romano 1994). The bootstrapped standard errors are very close to those reported in the paper.

[18] For example, we have prices for 1-year and 2-year zero-coupon bonds. Since a 2-year bond will become a 1-year bond after one year, the combination of a 2-year bond price and the 1-year bond price one year later can be used to calculate the annual return for the 2-year bond.

For the 10 portfolios in Panels C1 and C2 of Table 1, we observe the same two patterns as in Panel A2. First, longer-maturity bonds have higher CF betas than shorter-maturity bonds, and the difference in CF betas between the long- and short-maturity bonds is higher than that in DR betas. Second, for the same bond, the CF beta is always higher than the DR beta.[19,20]

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. Further, higher duration bonds have higher CF risk. Of course, we know that all these patterns are false, because Treasury bonds have no nominal CF risk. These false patterns stem from our limited ability to forecast expected returns, which in turn leads to 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 decompose bond *yield* (instead of actual returns) into three DR news components. The procedure we use is appropriate for our purpose because it exactly matches what has been done to the equity returns in Campbell and Vuolteenaho (2004a): the realized excess returns are used, and the DR and CF news are separated. The consistent treatment on both equity and bond makes the comparison meaningful.

The evidence from the Treasury bond market has direct implications on what we can infer from the equity market. The forecasting power in the bond market is much higher than that in the equity market. If anything, this finding suggests that the false patterns in the bond market are likely to be even more severe in the equity market.

3. 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 which portion of the estimated CF news is actual CF news and which portion is due to our limited ability to forecast expected returns. Nevertheless, consistent with the intuition from the

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[19] Note that the difference between long- and short-maturity betas is more likely to be significant than the difference between CF and DR betas for the same bond. The reason is as follows. Bond returns across different maturities are positively correlated. As a result, the variance of the difference between long- and short-maturity betas is smaller than the variance of long- or short-maturity betas. On the other hand, the CF news and DR news tend to be negatively related (since CF news is the residual). So the variance of the difference between CF and DR beta tends to be higher than the variance of CF or DR beta.

[20] Since the bond portfolios are rebalanced, there could be some CF "news" in the sense that the coupon rates vary slightly depending on the bonds involved. Indeed, in their Footnote 4, Campbell, Polk, and Vuolteenaho (2009) claim that we use data from bond funds that are traded and rebalanced and thus our decomposition results are "invalid." We have two reasons to believe that this is not a severe concern. First, we do not use bond funds. The bond portfolios (from either Ibbotson or CRSP) are constructed using Treasury bonds that are meant to capture the returns of the sections or the maturities. There is no trading-reduced rebalancing involved. If a bond leaves a portfolio, it is usually for predictable reasons (such as large deviation from the maturity range). Therefore, even if there are coupon changes, such changes are likely to be predictable and thus are not "news." In any case, such changes are unlikely to be the main cause driving the monotonic patterns in Table 1. Second, in Panel C1 we observe the same pattern for zero coupon bonds, in which case coupon rate changes are not involved.

Table 2
Variance decomposition of the equity market portfolio

Models	1	2	3	4	5	6	7	8
Excess return	+	+	+	+	+	+	+	+
Term spread	+	+	+	+	+	+	+	+
10-year PE ratio	+							
Value spread	+	+	+	+	+	+	+	+
1-year PE ratio			+					+
Dividend yield				+				
Book-to-market ratio					+			+
BM spread						+	+	
Stock variance								+
Corporate issue							+	+
Panel A: Monthly data (1929–2001)								
Variance of *CF* (%)	0.06	0.44	0.05	0.14	0.10	0.36	0.57	0.05
Variance of *DR* (%)	0.27	0.05	0.23	0.11	0.21	0.10	0.30	0.27
Cov(*CF, DR*) (%)	−0.01	−0.09	0.01	0.02	−0.01	−0.08	−0.28	−0.01
Panel B: Monthly data (1952–2001)								
Variance of *CF* (%)	0.04	0.21	0.06	0.04	0.11	0.20	0.21	0.06
Variance of *DR* (%)	0.09	0.02	0.06	0.11	0.04	0.02	0.06	0.05
Cov(*CF, DR*) (%)	0.02	−0.03	0.03	0.02	0.02	−0.02	−0.05	0.03
Panel C: Annual data (1929–2001)								
Variance of *CF* (%)	0.42	5.00	0.40	2.91	1.20	5.95	3.04	0.55
Variance of *DR* (%)	3.21	0.36	2.79	1.59	1.94	1.05	0.90	2.16
Cov(*CF, DR*) (%)	−0.14	−0.78	0.14	−0.44	0.14	−1.86	−0.60	0.13
Panel D: Annual data (1952–2001)								
Variance of *CF* (%)	0.33	2.30	0.55	0.48	1.29	2.64	2.50	0.67
Variance of *DR* (%)	1.32	0.17	0.92	2.03	0.50	0.28	0.50	0.79
Cov(*CF, DR*) (%)	0.46	0.07	0.57	−0.02	0.42	−0.16	−0.23	0.56

We report the variances and covariance of the CF news and DR news for the equity market portfolio. The plus signs indicate the state variables that are included in the VAR. Excess return refers to that of the equity market portfolio; term spread is the spread of the long-term over short-term taxable bond yield; 10-year PE ratio is the log 10-year smoothed S&P 500 price-earning ratio; Value spread is log book-to-market of small value stocks minus that of small growth stocks; 1-year PE ratio is the log one-year smoothed S&P 500 price-earning ratio; Dividend yield is the dividend-price ratio of the market portfolio; Book-to-market is that of the Dow Jones Industrial average; BM spread is the book-to-market spread (Liu and Zhang 2008); Stock variance is the sum of squared daily returns of S&P 500; Corporate issue is the ratio of 12-month moving sums of net issues of NYSE listed stocks divided by the market capitalization of NYSE stocks.

bond market, we know that different information sets (for the prediction of the expected returns) could change the estimated CF news and DR news, as well as subsequent conclusions based on the comparison between them. Therefore, here we alter the information set and examine (i) the variances of the DR news and CF news in the market portfolio, and (ii) the cross-sectional patterns of the two betas.

3.1 Variances of the market portfolio

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

Table 2 reports the variances of DR news and CF news of the equity market portfolio and their covariances. Panel A is based on monthly data covering 1929:01–2001:12, which is the sample period Campbell and Vuolteenaho (2004a) studied, and we use their data whenever possible. In the first column, where the benchmark case is used, the CF variance is 0.06% and the DR variance is 0.27%. Therefore, consistent with Campbell and Ammer (1993), DR news far exceeds CF news in driving aggregate equity returns. In the second column, we drop the PE ratio from the benchmark case and find that the CF variance is 0.44% and the DR variance is 0.05%—the trend is completely reversed.[21]

Why does the PE ratio make so much difference? As Campbell and Vuolteenaho (2004a) point out, the importance of any state variable depends on its persistence and its coefficient in VAR estimation. In the benchmark case, the return prediction coefficients (the first row of Γ) are as follows:

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

where $r_{M,t}$ is the excess return, TY_t is the term spread, PE_t is the 10-year PE ratio, and VS_t is the value spread. The coefficient for the PE ratio (−0.014) is not particularly high. However, this 10-year smoothed PE ratio is highly persistent: regressing this variable on its own lag yields a coefficient of 0.994 and an R-squared of 99.1%. As a result, the first row of λ, which considers the infinite sum, is [−0.398 0.011 − 0.883 − 0.284]; the PE ratio becomes the dominant factor due to its persistence. Clearly, *ceteris paribus*, the more persistent the PE ratio, the smaller the CF news. Given the small predictive power of the return equation (R-squared of 2.57%), very persistent state variables are needed to make the DR variance larger than the CF variance.

We then replace the 10-year PE ratio by similar variables that are known proxies for expected returns. In the fourth column of Table 2, we use the 12-month trailing dividend yield, which is more commonly used to predict equity returns (e.g., Campbell and Shiller 1988a; Campbell and Ammer 1993; Campbell and Mei 1993; Campbell and Vuolteenaho 2004b); we find the CF variance at 0.14% and the DR variance at 0.11%.

In the sixth column of Table 2, we use the book-to-market spread, defined as the book-to-market of value stocks minus that of growth stocks. We use this variable because Liu and Zhang (2008) argue that it is able to pick up the counter-cyclicality of the expected return more effectively than the value spread. We find that the inclusion of this variable makes the 10-year PE ratio insignificant, which is subsequently dropped. This variable also increases the statistical significance of every other variable; that is, the use of this variable (rather than the 10-year PE ratio) improves the predictive power of the VAR. Further, this variable is an intuitive proxy for expected return. Nevertheless,

[21] Note that the variance of the unexpected return of the market portfolio (= $var(CF) + 2 \times cov(CF,DR) + var(DR)$) is different for different specifications. This is because different models have different predictive powers, and the residual, which is the unexpected return, will be different.

this specification leads to a CF variance at 0.36% and a DR variance at 0.10%. We further add the corporate issue activity, defined as the 12-month moving sum of net issues by NYSE stocks divided by total market capitalization of NYSE stocks (Baker and Wurgler 2000), to the specification in Column 7. This combination yields the best predictive power at monthly frequency (*R*-squared at 3.5%), but the CF variance is still much higher.

Panel B of Table 2 reports the results for 1952–2001 (post Treasury-Fed Accord) to provide a better comparison with Campbell and Ammer (1993). Similar to Panel A, we see the flip of importance of the CF variance and DR variance depending on the VAR specification. For example, the use of a 1-year PE ratio (rather than the 10-year PE ratio) makes the CF variance equal to the DR variance. In the fifth column, using the book-to-market ratio (e.g., Kothari and Shanken 1997; Pontiff and Schall 1998; Lewellen 1999), obtained from Goyal and Welch (2008), leads to a CF variance much larger than the DR variance. Simply put, the relative importance of CF variance and DR variance is sensitive to minor changes of state variables. Panels C and D report the results using annual data and point to a similar flipping pattern.

We can use other model specifications to illustrate this flipping pattern; we only report the specifications in Table 2 because they represent seemingly equivalent proxies for expected returns. There is no clear reason why the 10-year PE ratio is a better proxy of expected return than, say, the 1-year PE ratio, the dividend yield, or the book-to-market, particularly when the 10-year PE ratio is not even stationary. More importantly, many of these variables have been alternatively used (e.g., Campbell and Shiller 1988a; Campbell and Ammer 1993; Campbell and Mei 1993; Vuolteenaho 2002; Campbell and Vuolteenaho 2004a, 2004b).

The finding that seemingly innocuous modifications can lead to different conclusions highlights the fragility of the approach. Theoretically, this approach works perfectly if we know the "true model." Empirically, almost all models have small predictive power, meaning that these models are far from the "true model" and are estimated with noise. The impact of the estimated coefficients on the infinite horizon is largely amplified through the persistence of the state variables. Our results indicate that minor modifications in the choice of the state variables can easily flip the patterns.

The relative magnitude of CF variance and DR variance has important implications. A related empirical literature, either directly or indirectly, debates about this relative importance (e.g., Roll 1988; Fama 1990; Stambaugh 1990; Cochrane 1992, 2008; Kothari and Shanken 1992; Campbell and Ammer 1993; Ang 2002; Lettau and Ludvigson 2005; Ang and Bekaert 2007; Chen 2008; Chen and Zhao 2008; Chen, Da, and Priestley 2008; Larrain and Yogo 2008). Given the flip we observe in Table 2, we are hesitant to draw any conclusion on the issue based on this method. Rather, the case in point is that the evidence provided through the variance decomposition approach might be more sensitive to the choice of state variables than one would normally expect.

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

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%)		
Two Beta 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%)	

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

3.2 Cross-sectional patterns

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

Table 3 is a brief replication of what is achieved in Campbell and Vuolteenaho (2004a). Panel A reports 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 not only decreases with size, but it also declines from growth to value firms. Because the two patterns largely cancel each other out with respect to returns, the CAPM beta is insignificant in the cross-section of returns; see also Ang and Chen (2007) and Fama and French (2006).

The CF betas and DR betas we calculate are very close to those in Campbell and Vuolteenaho (2004a).[22] 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; the trend is relatively stronger for the CF betas, as they are 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 large firms. Combined, the two betas explain 50% of the variation, compared to the meager 2% by the CAPM. Based on this evidence, Campbell and Vuolteenaho (2004a) conclude that it is CF beta, not DR beta, that matters. The DR betas would have suggested that value firms earn lower returns, contrary to the actual return pattern.

3.2.2 Replacing the benchmark case with similar variables. While Table 2 highlights the importance of a persistent 10-year PE ratio in driving the time series results in the decomposition approach, Table 4 explores the same specifications for the cross-section. We focus on the post-1963 period because the CAPM breaks down in this period.

Panel A of Table 4 shows that, when we exclude the PE ratio from the benchmark case, the CF beta significantly declines from growth to value firms. For example, the CF beta is 1.74 for small growth stocks and shrinks to 1.44 for small value stocks. The difference of -0.30 is highly significant with a standard error of 0.07. The same trend holds for all other portfolios. In addition, the magnitude of the CF betas is much larger than that of the DR betas, consistent with the results in Table 2 that, once the PE ratio is excluded, CF variance appears to be more important.

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

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

Table 4
Betas with a subset of or similar state variables as in Campbell and Vuolteenaho (2004a)

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

Panel A1: 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	[0.07]
4	1.37		1.29		1.17		1.07		1.20		−0.17	[0.07]
Large	1.09		1.09		0.95		0.91		0.97		−0.12	[0.06]
Diff	−0.65	[0.10]	−0.42	[0.09]	−0.44	[0.08]	−0.44	[0.07]	−0.47	[0.07]		
β_{DR}	Growth		2		3		4		Value		Diff	
Small	−0.03		−0.07		−0.12		−0.13		−0.18		0.15	[0.03]
2	−0.05		−0.14		−0.16		−0.17		−0.19		0.14	[0.03]
3	−0.08		−0.15		−0.16		−0.19		−0.19		0.11	[0.03]
4	−0.06		−0.15		−0.16		−0.15		−0.19		0.13	[0.03]
Large	−0.05		−0.12		−0.11		−0.15		−0.17		0.12	[0.03]
Diff	0.02	[0.05]	0.05	[0.04]	−0.01	[0.04]	0.02	[0.03]	0.01	[0.03]		

Panel A2: Cross-sectional regression

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

Panel B1: VAR variables include the excess equity market return, term spread, log 1-year PE ratio, and value spread

β_{CF}	Growth		2		3		4		Value		Diff	
Small	0.33		0.27		0.24		0.23		0.24		−0.09	[0.02]
2	0.28		0.24		0.21		0.19		0.20		−0.08	[0.03]
3	0.24		0.21		0.20		0.17		0.19		−0.05	[0.03]
4	0.22		0.21		0.19		0.16		0.18		−0.04	[0.03]
Large	0.15		0.17		0.14		0.14		0.14		−0.01	[0.02]
Diff	−0.18	[0.04]	−0.10	[0.03]	−0.10	[0.03]	−0.09	[0.03]	−0.10	[0.03]		

Panel B2: VAR variables include the excess equity market return, term spread, dividend yield, and value spread

Small	0.98		0.87		0.81		0.80		0.87		−0.11	[0.04]
2	0.91		0.84		0.80		0.76		0.83		−0.08	[0.04]
3	0.87		0.81		0.74		0.71		0.77		−0.10	[0.04]
4	0.77		0.77		0.71		0.66		0.74		−0.03	[0.04]
Large	0.63		0.66		0.58		0.58		0.61		−0.02	[0.04]
Diff	−0.35	[0.06]	−0.21	[0.05]	−0.23	[0.04]	−0.22	[0.04]	−0.26	[0.04]		

Panel B3: VAR variables include the excess equity market return, term spread, book-to-market ratio, and value spread

Small	0.72		0.59		0.52		0.52		0.55		−0.17	[0.04]
2	0.63		0.54		0.50		0.48		0.52		−0.11	[0.04]
3	0.59		0.51		0.46		0.44		0.47		−0.12	[0.04]
4	0.53		0.48		0.44		0.39		0.43		−0.10	[0.04]
Large	0.42		0.42		0.36		0.35		0.36		−0.06	[0.03]
Diff	−0.30	[0.05]	−0.17	[0.05]	−0.16	[0.04]	−0.17	[0.04]	−0.19	[0.04]		

Panel B4: VAR variables include the excess equity market return, term spread, book-to-market spread, corporate issue, and value spread

Small	0.64		0.52		0.46		0.47		0.50		−0.14	[0.08]
2	0.55		0.48		0.45		0.43		0.48		−0.07	[0.08]
3	0.53		0.47		0.41		0.39		0.44		−0.09	[0.08]
4	0.46		0.44		0.40		0.34		0.39		−0.07	[0.08]
Large	0.38		0.39		0.33		0.31		0.33		−0.05	[0.07]
Diff	−0.26	[0.11]	−0.13	[0.10]	−0.13	[0.09]	−0.16	[0.08]	−0.17	[0.08]		

(*Continued overleaf*)

Table 4
(*Continued*)

β_{CF}	Growth		2		3		4		Value		Diff	
Panel B5: VAR variables include the excess equity market return, term spread, updated 10-year smoothed PE ratio, and value spread												
Small	0.34		0.27		0.24		0.23		0.25		−0.09	[0.03]
2	0.29		0.24		0.22		0.19		0.21		−0.08	[0.03]
3	0.25		0.22		0.20		0.20		0.17		−0.08	[0.03]
4	0.23		0.21		0.19		0.16		0.18		−0.05	[0.03]
Large	0.16		0.17		0.15		0.14		0.14		−0.02	[0.02]
Diff	−0.18	[0.04]	−0.10	[0.03]	−0.09	[0.03]	−0.09	[0.03]	−0.11	[0.03]		

Campbell and Vuolteenaho (2004a) use four state variables in their VAR system: excess equity market return, term spread, 10-year smoothed PE ratio, and the value spread. In Panel A, the 10-year PE ratio is excluded; we report discount rate and cash flow betas, as well as cross-sectional regression coefficients. In Panels B1–B4, we report the cash flow betas when the 10-year PE ratio is replaced, in sequence, by (i) 1-year PE ratio, (ii) dividend yield, (iii) book-to-market ratio, and (iv) the book-to-market spread plus the corporate issue. The standard errors of the differences in the betas between large and small, as well as value and growth firms are obtained through bootstrapping 10,000 realizations. This table only reports results during 1963:07–2001:12.

Two patterns are noteworthy in the cross-sectional regression in Panel A2 of Table 4. First, the CF beta has a significantly positive coefficient, but it does not mean that value stocks earn higher returns because of their higher CF betas; in fact, Panel A1 shows that these stocks 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 the book-to-market ratio. Second, the R-squared is 52%, which is higher than that in the benchmark case. Therefore, the exclusion of the PE ratio does not lead to a drop in the cross-sectional explanatory power, but it leads to a reversal of CF beta trend for value stocks.

In Panels B1–B4 of Table 4, we study various cases where the 10-year PE ratio is replaced by similar proxies for the expected return, including: (i) the 1-year PE ratio, (ii) the dividend yield, (iii) the book-to-market ratio, and (iv) the book-to-market spread plus the corporate issue activity. The rationale for using these specifications has been explained previously. For brevity we only report the cross-sectional pattern of CF betas; in all cases the DR beta declines from value to growth stocks. All four panels show a declining trend of the CF beta from growth to value stocks. Therefore, similar to Table 2, the cross-sectional pattern is very sensitive to minor alterations in model specification, but the pattern is more stable in this case as they all point to a declining trend of CF beta from growth to value stocks.

Finally, the 10-year smoothed PE ratio in the benchmark case is from Shiller (2000), which has been updated by Shiller. We downloaded the data from Shiller's website. Since the monthly earnings data are interpolated from quarterly data, there is a look-ahead bias of up to two months; we thus lag the updated 10-year smoothed PE ratio by two months. When we use this new variable to replace the PE ratio in the benchmark case, the trend of the CF beta from growth stocks to value stocks is again reversed from the benchmark case, as is shown in Panel B5. The two PE ratios have a correlation of

92%. They are not identical for two possible reasons. First, the data have been updated by Shiller. Second, we use a two-month lag scheme, while Campbell and Vuolteenaho (2004a) might have used a slightly different scheme.

How could two similarly persistent PE ratios (both with autocorrelation at 99%) yield opposite beta patterns? When the benchmark variables are used, the estimated return prediction equation (suppressing the intercept term) is reported in Equation (21). The corresponding coefficients that reflect how current innovations affect equity return, $e1'\lambda$, are [−0.398 0.011 −0.883 −0.284]. When we use our version of the PE ratio, the prediction equation is

$$r_{M,t+1} = 0.095 \times r_{M,t+1} + 0.006 \times TY_t - 0.011 \times PE_t - 0.008 \times VS_t + u_{1t}. \tag{22}$$

Only the coefficient on the value spread is "largely" affected (from −0.013 in Equation (21) to −0.008). However, the corresponding $e1'\lambda$, is [−0.372 0.015 −0.843 −0.077]. It is clear that the importance of the value spread variable has largely changed relative to other variables, leading to cross-sectional betas that are drastically different from the benchmark case. We also find that with the updated benchmark case, the R-squared has dropped sharply from 50% to 12%. In other words, even in the benchmark case, once we use a slightly different PE ratio, the trend of CF betas is reversed, and the explanatory power of the cross-sectional regression largely disappears.

Therefore, Tables 2 and 4 show how the return decomposition approach works and its fragility. The approach works through a combination of VAR coefficients, which are usually estimated with noise, and highly persistent predictive variables. Without questioning the stationarity issue of the state variables, minor modifications of the choice of the state variables (and thus the VAR coefficients) and their persistence can easily flip the findings.

4. Some Potential Remedies

The relative importance of CF/DR news in the time series and cross-section of security returns is an important issue. The decomposition by Campbell and Shiller (1988a) is intuitive in theory. Empirically, the residual-based decomposition is agonizing since minor changes in model specification can lead to *opposite* conclusions. Here we provide further analysis to search for potential remedies for such high sensitivity.

4.1 Direct modeling of the CF news

Naturally, one thinks of modeling both CF and DR news in the VAR. Such a procedure amounts to breaking the CF news in the current decomposition approach into the directly modeled CF news and model noise. This method acknowledges the fact that there is a noise component in the stock return that cannot be explained; further, it enables the comparison of the modeled CF news and DR news on equal footing through their relative predictability. We explore this approach using two different cash flow proxies: dividend growth rate and earning on book equity (also called ROE, return on equity).

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

$$e_{t+1} = e_{CF,t+1} - e_{DR,t+1} + residual, \tag{23}$$

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 returns do not necessarily predict dividend growth rate.[23] 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

$$e_{CF,t+1} = e1'\lambda_3\varpi_{t+1}, \tag{24}$$

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 of the state variables on expected future dividend growth. We separate the two terms because the current CF news relies relatively less on the specification of the VAR system while the future CF news depends critically on λ_3, and thus on the estimated coefficients of the VAR system. Finally, we construct the residual component after the CF news and DR news are both considered.

In Panel A of Table 5, we report the betas for the 25 portfolios. We use annual data to mitigate the seasonality of dividend growth. The state variables in the return VAR are the same as those in the benchmark case. The state variables in the dividend growth rate VAR include dividend growth rate (of the market portfolio), market equity return, and dividend yield. These variables are included because of their ability to forecast dividend growth.

As is clear in the panel, value stocks have lower current CF betas and future CF betas, and thus lower total CF betas; they also have lower DR betas as found before. However, value stocks have higher residual betas. Modeling the DR news but backing out the CF news as the residual is equivalent to combining the CF betas and the residual betas, and the combined betas are therefore higher for value stocks. The cross-sectional pattern of the directly constructed CF betas is opposite to the benchmark case, while the pattern of the combined

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

Table 5
Betas when CF news is directly modeled

Panel A: Dividend growth rate as the cash flow proxy

	Growth	2	3	4	Value	Growth	2	3	4	Value
			β_{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

Panel B: ROE as the cash flow proxy

	Growth	2	3	4	Value	Growth	2	3	4	Value
			β_{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

We directly model both the DR news and CF 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 includes the same variables as in the benchmark case. We use two cash flow proxies: dividend growth rate and earnings 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 includes 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 impact of the current innovations of state variables on expected future cash flow growth. 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 reports the case for dividend growth rate; Panel B reports the case for ROE.

(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.[24] This exercise points to the difficulty of drawing meaningful conclusions using the residual-based return decomposition approach.

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

4.1.2 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., Chen, Da, and Priestley 2008). There is another way to decompose returns and avoid using dividend-related measures. In particular, the derivation by Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003) suggests that

$$e_{t+1} = (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=0}^{N} \rho^j ROE_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=1}^{N} \rho^j r_{t+1+j}, \qquad (25)$$

where e_{t+1} is the unexpected equity return and ROE_{t+1+j} is the log return on book equity. This equation is symmetric to Equation (1) except that we have replaced dividend growth rate by *ROE*. Just like the case of dividend growth rate, we assume that equity returns can be predicted using a VAR involving the same state variables as in the benchmark case. In addition, ROE can be estimated using a VAR including ROE, excess equity return, and book-to-market. We use the merged CRSP-Compustat dataset to create a market portfolio and calculate the ROE and book-to-market of the market portfolio. When the book equity is not available in Compustat, we resort to Moody's book equity, as used in Davis, Fama, and French (2000). The final data with market ROE and book-to-market is at the annual frequency covering the 1930–2001 period. We then apply the return decomposition and report the results in Panel B of Table 5.

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

[24] 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.

4.2 Bayesian model averaging approach

Econometricians have long warned of the danger of drawing conclusions based on certain specifications but ignoring others. Avramov (2002) and Cremers (2002) propose a Bayesian model averaging approach to mitigate the problem of model uncertainty. Following their approach, we first choose a large pool of state variables known to predict stock returns. We assign equal prior probability to each possible combination of these state variables (i.e., each model); we update the posterior probability of each model according to the formulas in Avramov (2002) and Cremers (2002) that characterize the success of return predictability. For each model, we estimate the CF/DR news (variances) of the market portfolio and the portfolio betas. Finally, the expected variances of CF/DR news of the market portfolio and the expected CF/DR betas of portfolios are calculated using the posterior probability. Intuitively, such an approach weighs the coefficients of each model based on its success to predict returns.

Table 6 reports the CF betas. Panel A has 11 state variables, including the four in Campbell and Vuolteenaho (2004a). Using Avramov's model, there is a positive, yet very small, trend of CF beta from growth to value stocks. For example, for the second-to-smallest size groups, CF beta increases from 0.39 to 0.46; the corresponding numbers in Campbell and Vuolteenaho (2004a) are from 0.04 to 0.12. For the medium-size portfolios, CF beta increases from 0.40 to 0.44; the corresponding numbers in Campbell and Vuolteenaho (2004a) are from 0.03 to 0.13. In addition, using Cremer's model, the trend is completely flat across portfolios.

Therefore, when the Bayesian model averaging approach is used, and when we add more predictive variables to the benchmark case, the results in Campbell and Vuolteenaho (2004a) are much weakened. This finding is intuitive. Since most models do not lead to an increasing pattern of CF beta from growth to value stocks, considering model uncertainty will only weaken the benchmark case.

Panel B of Table 6 contains the same set of variables as in Panel A except that we replace the 10-year PE ratio by the 1-year PE ratio. Both Avramov's and Cremer's methods lead to CF betas either slightly decreasing or flat from growth to value stocks. In Panel C we replace the 10-year PE ratio by the dividend yield; in Panel D we replace the value spread by the book-to-market spread and the market-to-book spread, following Liu and Zhang (2008). The results in Panels C and D are similar to those in Panel B. In general, mirroring Table 4, when the 10-year PE ratio is replaced by close substitutes for expected returns, or when the value spread is replaced, the trend of CF beta from growth to value stocks is either declining or flat.

We thus can learn two things from using the Bayesian model averaging approach. First, considering model uncertainty in the residual-based decomposition approach largely weakens the benchmark case, consistent with our earlier finding that most models do not lead to higher CF betas for value stocks.

Table 6
Cash flow betas with Bayesian model averaging method

	Avramov					Cremers ($\phi = 3.25$)				
β_{CF}	Growth	2	3	4	Value	Growth	2	3	4	Value
Panel A: VAR variables include the excess equity market return, term spread, 10-year PE ratio, value spread, credit spread, long-term corporate bond return, book-to-market ratio, 3-month T-bill rate, inflation, corporate issuing activity, and stock variance.										
Small	0.41	0.39	0.41	0.41	0.45	0.51	0.47	0.46	0.46	0.49
2	0.39	0.41	0.42	0.44	0.46	0.47	0.47	0.47	0.47	0.49
3	0.40	0.42	0.41	0.42	0.44	0.47	0.47	0.45	0.44	0.47
4	0.37	0.41	0.41	0.40	0.44	0.44	0.45	0.44	0.42	0.46
Large	0.30	0.36	0.32	0.34	0.36	0.35	0.39	0.34	0.35	0.36
Panel B: VAR variables are the same as in Panel A except that the 10-year PE ratio is replaced by the 1-year PE ratio.										
Small	0.55	0.50	0.49	0.48	0.51	0.62	0.54	0.52	0.51	0.54
2	0.52	0.50	0.49	0.49	0.51	0.57	0.54	0.51	0.51	0.53
3	0.51	0.49	0.47	0.45	0.48	0.55	0.52	0.49	0.46	0.50
4	0.48	0.47	0.46	0.44	0.47	0.51	0.49	0.47	0.44	0.48
Large	0.37	0.41	0.35	0.36	0.37	0.40	0.42	0.37	0.36	0.38
Panel C: VAR variables are the same as in Panel A except that the 10-year PE ratio is replaced by the dividend-yield.										
Small	0.96	0.89	0.86	0.85	0.92	1.02	0.92	0.88	0.87	0.93
2	0.92	0.90	0.87	0.87	0.92	0.97	0.92	0.88	0.86	0.92
3	0.92	0.88	0.83	0.80	0.88	0.96	0.89	0.83	0.79	0.87
4	0.83	0.84	0.80	0.77	0.85	0.86	0.85	0.80	0.75	0.84
Large	0.69	0.74	0.65	0.64	0.69	0.70	0.74	0.65	0.63	0.68
Panel D: VAR variables are the same as in Panel A except that the value spread is replaced by the book-to-market spread and the market-to-book spread.										
Small	0.66	0.57	0.53	0.51	0.53	0.68	0.59	0.53	0.52	0.54
2	0.61	0.53	0.49	0.47	0.50	0.63	0.54	0.49	0.48	0.50
3	0.57	0.49	0.45	0.42	0.46	0.58	0.50	0.46	0.42	0.46
4	0.52	0.47	0.43	0.39	0.43	0.53	0.47	0.43	0.39	0.43
Large	0.38	0.39	0.33	0.31	0.33	0.39	0.39	0.33	0.31	0.33

We apply the Bayesian model averaging method, following Avramov (2002) and Cremers (2002), to a large set of predictive variables. In particular, we assign equal prior probability to each combination of state variables, but update the posterior probability according to the predictability of market excess returns. We then report the expected cash flow betas of 25 size and book-to-market portfolios using the posterior probability. The first three panels vary only because we replace the 10-year PE ratio by either the 1-year PE ratio or the dividend yield. In Panel D, we replace the value spread by the book-to-market spread and the market-to-book spread, following Liu and Zhang (2008).

Second, even with a large set of state variables, the results are still sensitive, albeit less dramatic, to close substitutes of the PE ratio or of the value spread.

4.3 Principal component analysis

Another way to deal with model uncertainty is to apply principal component analysis to a large set of state variables that can predict stock returns. The idea is to recover the first few principal components (five in this case) from the information set, thus shrinking the dimension of state variables. We then use these principal components as state variables in VAR.

The results, reported in Table 7, are highly consistent. In all four panels representing the same cases as in Table 6, there is a clear downward trend of CF beta from growth stocks to value stocks. This negative trend is the smallest

Table 7
Cash flow betas with principal component analysis

β_{CF}	Growth		2		3		4		Value		Diff	
Panel A: VAR variables include the excess equity market return, term spread, 10-year PE ratio, value spread, credit spread, long-term corporate bond return, book-to-market ratio, 3-month T-bill rate, inflation, corporate issuing activity, and stock variance.												
Small	0.24		0.18		0.14		0.14		0.15		−0.09	[0.03]
2	0.16		0.13		0.12		0.09		0.11		−0.05	[0.03]
3	0.15		0.12		0.09		0.07		0.09		−0.06	[0.03]
4	0.14		0.09		0.09		0.04		0.06		−0.08	[0.03]
Large	0.07		0.07		0.05		0.06		0.04		−0.03	[0.03]
Diff	−0.17	[0.04]	−0.11	[0.04]	−0.09	[0.03]	−0.08	[0.03]	−0.11	[0.03]		
Panel B: VAR variables are the same as in Panel A except that the 10-year PE ratio is replaced by the 1-year PE ratio.												
Small	0.53		0.40		0.32		0.30		0.30		−0.23	[0.03]
2	0.43		0.31		0.26		0.21		0.23		−0.20	[0.03]
3	0.38		0.26		0.21		0.15		0.19		−0.19	[0.03]
4	0.35		0.23		0.19		0.12		0.14		−0.21	[0.03]
Large	0.22		0.17		0.13		0.11		0.09		−0.13	[0.03]
Diff	−0.31	[0.04]	−0.23	[0.04]	−0.19	[0.03]	−0.19	[0.03]	−0.21	[0.03]		
Panel C: VAR variables are the same as in Panel A except that the 10-year PE ratio is replaced by the dividend-yield.												
Small	1.05		0.89		0.78		0.77		0.81		−0.24	[0.04]
2	0.93		0.80		0.74		0.67		0.74		−0.19	[0.04]
3	0.88		0.75		0.66		0.60		0.67		−0.21	[0.04]
4	0.79		0.69		0.62		0.53		0.61		−0.18	[0.04]
Large	0.60		0.58		0.49		0.47		0.49		−0.11	[0.04]
Diff	−0.45	[0.06]	−0.31	[0.05]	−0.29	[0.05]	−0.30	[0.04]	−0.32	[0.04]		
Panel D: VAR variables are the same as in Panel A except that the value spread is replaced by the book-to-market spread and the market-to-book spread.												
Small	0.47		0.38		0.32		0.32		0.33		−0.14	[0.02]
2	0.41		0.30		0.26		0.25		0.28		−0.13	[0.02]
3	0.35		0.27		0.24		0.21		0.24		−0.11	[0.02]
4	0.31		0.26		0.22		0.19		0.21		−0.10	[0.02]
Large	0.20		0.20		0.17		0.15		0.16		−0.04	[0.02]
Diff	−0.27	[0.03]	−0.18	[0.03]	−0.15	[0.03]	−0.17	[0.02]	−0.17	[0.02]		

We retrieve the first five principal components from a large set of predictive variables and use them as the state variables. We report the cash flow betas of 25 size and book-to-market portfolios. The first three panels vary only because we replace the 10-year PE ratio by either the 1-year PE ratio or the dividend yield. In Panel D, we replace the value spread by the book-to-market spread and the market-to-book spread, following Liu and Zhang (2008). The standard errors of the differences in the cash flow betas between large and small, as well as value and growth firms, are obtained through bootstrapping 10,000 realizations. We present results only for the 1963–2001 period.

and insignificant in Panel A, where the benchmark variables are included, but is much larger and mostly significant in other cases when the 10-year PE ratio is replaced by either the 1-year PE ratio or by the dividend yield, or when the value spread is replaced. Overall, then, when the principal component analysis is conducted, growth firms tend to have higher CF betas, or at least do not have lower CF betas.

4.4 Some motivated choices

It could be argued that, without knowing the true model, we should pick the set of predictive variables best motivated by economic reasons. This approach is certainly helpful, but has limitations. Almost all known return predictors are

Table 8
Cash flow betas with alternative specifications

β_{CF}	Growth		2		3		4		Value		Diff	
Panel A: VAR variables: excess equity market return, term yield, dividend yield, credit spread, and risk-free rate.												
Small	1.47		1.28		1.18		1.14		1.18		−0.29	[0.05]
2	1.39		1.23		1.13		1.08		1.12		−0.27	[0.05]
3	1.34		1.15		1.05		0.96		1.04		−0.30	[0.05]
4	1.21		1.07		0.99		0.93		1.02		−0.19	[0.05]
Large	0.93		0.91		0.77		0.74		0.77		−0.16	[0.04]
Diff	−0.54	[0.07]	−0.37	[0.06]	−0.41	[0.05]	−0.40	[0.05]	−0.41	[0.05]		
Panel B: VAR variables include excess equity market return, term spread, PE ratio, value spread, cay, risk-premium factor, and volatility factor.												
Small	0.48		0.43		0.40		0.40		0.44		−0.04	[0.07]
2	0.40		0.37		0.38		0.35		0.39		−0.01	[0.07]
3	0.35		0.34		0.32		0.33		0.36		0.01	[0.07]
4	0.33		0.32		0.32		0.32		0.35		0.02	[0.12]
Large	0.24		0.25		0.26		0.25		0.22		−0.02	[0.12]
Diff	−0.24	[0.14]	−0.18	[0.14]	−0.14	[0.09]	−0.15	[0.09]	−0.22	[0.10]		

We study the cross-sectional pattern of cash flow betas when alternative specifications are used. In Panel A, we use the macro variables by Petkova (2004) that provide intuitive interpretations on the Fama-French factors. In Panel B, we add variables shown by Lettau and Ludvigson (2001a, 2001b) and Ludvigson and Ng (2005) to exhibit good predictive power for equity returns. Panel B uses quarterly data because these variables are available only at quarterly frequency. The standard errors of the differences in the cash flow betas between large and small, as well as value and growth firms, are obtained through bootstrapping 10,000 realizations. We present results only for the 1963–2001 period.

related to the macroeconomy, and thus can be easily motivated as meaningful. Which economic model is more meaningful becomes a matter of taste. One contribution of this study is to show that, given the nature of the residual-based return decomposition approach, minor differences of such tastes can easily lead to opposite conclusions—the economic conclusions based on a certain model, as is almost always the case in the current literature, must be interpreted with extreme caution.

In Table 8 we explore two cases that seem to be well motivated. Panel A considers the set of variables from Petkova (2006) that have clear macroeconomic meanings and can absorb the Fama-French (1993) risk factors: the excess market return, the term spread, the dividend yield, the credit spread (Baa over Aaa yield), and the risk-free rate. In this case, the CF beta decreases significantly from growth to value stocks.

Panel B of Table 8 explores the case in which we can largely increase the predictive power on equity returns in the first-stage VAR regression. It adds three state variables—*cay* from Lettau and Ludvigson (2001a, 2001b) and the risk-premium factor and the volatility factor from Ludvigson and Ng (2007)—to the benchmark case. These state variables increase the R-squared of the equity return prediction equation from 2.57% in Campbell and Vuolteenaho (2004a) to 14% (at quarterly frequency). Panel B indicates that the inclusion of these variables wipes out the cross-sectional patterns of the CF betas in the benchmark case.

The above two examples suggest that it is very easy to find model specifications that are well motivated, either economically or statistically, but reach conclusions very different from the benchmark case. We do not mean to say that these models are superior to the benchmark case. Rather, the case in point is that conclusions based on any particular model, no matter how well motivated the model is, must be drawn with caution.

4.5 Summary of results

Our analysis in this section suggests that the cross-sectional pattern of CF betas in Campbell and Vuolteenaho (2004a) appears to be a special case conditional on their model specification. For most specifications, value stocks do not have higher CF betas than growth stocks do.

In untabulated results, we also find that the relative importance of the CF/DR variances of the market portfolio varies depending on the information set and on the sample periods. This is the case regardless of whether one uses direct modeling of CF news, the Bayesian model averaging approach, the principle component analysis, or special specifications motivated by economic reasons. Unlike the cross-sectional patterns of CF betas, however, the relative importance of the CF/DR variances of the market portfolio flips frequently to such a degree that we cannot conclude what the common pattern for most specifications is.

Our results also lead to the following set of suggestions regarding how to conduct return composition.

First, while it is important to search for predictive variables well motivated by economic reasons, it is far from enough. The reason is that most predictive variables are related to the macroeconomy and thus are "well motivated." We contribute to the literature by showing how easy it is to draw opposite conclusions based on seemingly equally motivated models. Researchers should be aware of such a danger when digesting the conclusions based on a certain model. Extensive robustness checks with respect to model sensitivity are necessary before one can put faith into such conclusions.

Second, a natural approach is to model both DR and CF in VAR. With such an approach, the unexpected return will be decomposed into DR news, directly modeled CF news, and residual news. Though we still do not know the nature of the residual news, we can at least compare the DR news and CF news on equal footing.

Third, to mitigate model uncertainty, one can use the Bayesian model averaging approach (Avramov 2002; Cremers 2002). The idea is to first select a large set of predictive variables, any combination of which constitutes a potential model. The importance of each model is weighed by its success to predict stock returns, and the conclusions are weighed accordingly. Another approach is to first recover the principal components of a large set of predictive variables, and then use them to predict stock returns (e.g., Ludvigson and Ng 2007).

5. Further Robustness Checks

5.1 Industry portfolios

If the CF beta is important for the purpose of calculating the cost of equity, it should be priced into most portfolios. Thus far, our tests center on 45 portfolios, most of which are sorted by size and market-to-book ratio. Such a procedure is, to some extent, subject to the criticism that the patterns might be driven by firm characteristics instead of systematic risks (Daniel and Titman 1997, 2006), or by mechanical portfolio formation procedures (Lewellen, Nagel, and Shanken 2006).

One way to test the robustness of the CF beta is to investigate whether it is priced in the 48 industry portfolios defined by Fama and French (1997). In untabulated results, we calculate CF and DR betas using the benchmark case. We find that industries with lower CF betas tend to have higher equity returns. Accordingly, running a cross-sectional regression of the average excess returns on the two betas, we find that the CF beta is priced in the wrong way: the regression coefficient is significantly negative. This suggests 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.

5.2 Post-1952 data

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

5.3 Other robustness checks

For brevity we discuss the following additional results without reporting. As in Campbell and Vuolteenaho (2004a), we provide further robustness checks in the following dimensions: (i) the magnitude of ρ, (ii) the data frequency, (iii) additional VAR lags, and (iv) conditional betas. We find that changing ρ does not change the results. We have results (Table 5 and Panel B of Table 8) indicating that using annual or quarterly data does not alter the conclusions. In addition, we use standard statistical criteria to add more lags to the state variables and find little changes to current conclusions. Furthermore, we adopt a 36-month rolling window to estimate the conditional CF betas and DR betas for each portfolio. We find the same conclusions.

The persistence of the state variables has been a major source of instability and statistical concerns. Thus, one natural thought is to use the changes, rather than the levels, of the state variables to predict returns. We have explored this route, and the results are highly consistent: (i) CF news is more important than DR news for the market portfolio and (ii) value stocks have lower CF betas. The reason is as follows. In the return decomposition literature, the effect of the DR news is calculated by combining the small predictive coefficient with the highly persistent predictive variables. The changes of the set of independent variables do not predict returns very well, nor are they persistent. As a result, the DR news is small, and the CF news acts pretty much like return itself.

6. Conclusions

The relative role of discount rate (DR) news and cash flow (CF) news in driving the time-series and cross-sectional variations of returns is a central theme in asset pricing. One popular approach is to model DR news through predictive regressions, and back out the CF news as the difference between unexpected returns and DR news. Using this approach, some important conclusions have been drawn, including (i) that the variance of the DR news is larger than that of the CF news for the market portfolio, consistent with the claim that the time variation of the equity risk premium plays a central role in driving aggregate returns; (ii) that value stocks earn higher returns because they have higher CF betas; and (iii) that, for the purpose of calculating the cost of equity, the more important measure of risk is the CF beta, not the total beta.

We argue that this approach has a serious limitation and should be followed with caution. Theoretically, the approach works perfectly if one knows the "true model" to predict returns. Empirically, however, the DR news cannot be accurately estimated because of the small predictive power, and the CF news, as the residual, inherits the large misspecification error of the DR news. The relative role of DR/CF news is inevitably a function of the selected predictive variables.

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

We then examine equity returns. We show that minor changes of the predictive variables can easily change prior conclusions regarding the relative role of DR/CF news in driving the time-series and cross-sectional variations of returns. We propose to model both DR news and CF news directly, which amounts to dividing the CF news in the current literature into the directly modeled CF news and the residual news. We find that value firms have both lower modeled CF betas and DR betas, but higher residual betas, indicating that the results in the current literature are driven by the residual news. Several other potential solutions, including the Bayesian model averaging approach (Avramov 2002; Cremers 2002) and the principal component analysis, are also explored.

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