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This is the authors' accepted and refereed manuscript to the article published in
***Journal of Financial and Quantitative Analysis*, 47(2012)5: 1003-1028**

DOI: <http://dx.doi.org/10.1017/S0022109012000427>

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Dividend Growth, Cash Flow and Discount Rate News

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Abstract

Using a new variable based on a model of dividend smoothing, we find dividend growth is highly predictable and cash flow news contributes importantly to return variability. Cash flow betas derived from this predictability are central to explaining the size effect in the cross section of returns. However, they do not explain the value effect; this is explained by noise betas. We also find that the relative importance of cash flow news in explaining recent stock price run-ups and subsequent falls increases when cash flow news is estimated directly.

I. Introduction

Investors' revisions to forecasts of future cash flows and discount rates are a central issue in understanding stock price movements. At present, the empirical evidence points to the conclusion that prices are driven mainly by revisions to discount rates and that cash flows are largely unpredictable.¹ The current thinking on this topic is best expressed by Cochrane (2010), page 1, when discussing the development of the literature over the last 40 years:

“Most views of the world changed 100%: we thought 100% of the variation in the market dividend yields was due to variation in expected cash flows; now we know 100% is due to variation in discount rates.”

That most of the empirical evidence points to the fact that dividend growth appears unpredictable and all the movement in the dividend-price ratio is driven by news about future discount rates is a remarkable and troubling finding.

While cash flow news seems to be less important in terms of the time series variability of returns, it has a central role in explaining the cross section of returns. Campbell and Vuolteenaho (2004) extend the standard decomposition of the market return into cash flow news and discount rate news and show that the CAPM beta can be similarly decomposed into a cash flow beta and a discount rate beta. Since dividend growth is difficult to predict, they choose a set of instruments to predict returns and back out cash flow news as the residual. Cash flow betas are

¹There is a long literature on the predictability of returns and dividend growth (see, for example, Ang (2002), Ang and Bekaert (2007), Campbell and Shiller (1988), Campbell (1991), Cochrane (1992), Cochrane (2005), Cochrane (2008), Cochrane (2010), Goyal and Welch (2003), Goyal and Welch (2008), and Lettau and Van Nieuwerburgh (2008).) Campbell (1991) documents that the dividend-price ratio has very little predictive power for dividend growth. Cochrane (1992) finds that variation in the dividend-price ratio is almost entirely driven by variation in expected returns, suggesting that dividend growth can effectively be treated as constant. More recently, Cochrane (2008) shows that the dividend-price ratio cannot predict dividend growth and argues that variations in the dividend-price ratio must therefore forecast returns. These findings tend to be reinforced by the finding that when backing cash flow news out as the residual from the return decomposition (see Campbell (1991)), discount rate news dominates in terms of explaining the return variance (see, for example, Campbell (1991), Campbell and Ammer (1993) and Vuolteenaho (2002).)

then shown to be able to explain the value premium puzzle. These two findings regarding the role of cash flow news in the time series and the cross section of stock returns raise an intriguing question: if discount rate news is the main driver of asset returns in the time series, because cash flows are basically unpredictable and thus grow at a constant rate, why does cash flow news in the form of cash flow betas have such an important role in the cross section of returns? That is, when cash flows grow at a constant rate there should be no cash flow news.

Chen and Zhao (2009) provide an important insight into the possible origins of this puzzle. They show that because return predictability regressions have small predictive power and are sensitive to the choice of forecasting instruments, backed-out cash flow news inherits any, potentially large, misspecification error in the estimation of discount rate news. This leads to conflicting empirical results regarding the role of cash flow news in explaining the time series and cross sectional patterns in returns. Chen and Zhao (2009) propose that in order to obtain more reliable results regarding the role of cash flow news and discount rate news, it is necessary to estimate cash flow news directly. However, they do not investigate which variable(s) can best forecast cash flows. Consequently, it is not clear to what extent the time series and cross sectional variation in returns is driven by cash flow news and discount rate news.

In this paper, we use a novel variable to show that dividend growth is strongly predictable. This places us in a position to more safely consider the role of cash flow news in both the time series and cross section of returns. Armed with a model that forecasts dividend growth well, we attempt to answer the following questions: i) what is the extent of dividend growth predictability vis a vis stock return predictability; ii) does the relative contribution of cash flow and discount rate news to return variance change when we can forecast dividend growth and thereby estimate cash flow news directly;² iii) does estimating cash flow news directly alter the magnitude of

²Chen and Zhao (2010) also focus on understanding the role of cash flow news in stock price movements using analysts forecasts of earnings to measure cash flow news rather than focusing on predictive regressions. As we shall see, our results, using predictive regressions, show that cash flows are an important determinant of the time series variations in stock prices, consistent with the findings in Chen and Zhao (2010) and Larrain and Yogo (2008), who find that movements in the net payout ratio are driven by movements in expected cash flow growth and not movements in discount rates.

cash flow and discount rate betas; iv) does estimating cash flow news directly affect the cross sectional patterns in the betas; and v) what are the prices of risk for the betas. Showing that dividend growth is predictable and addressing these questions forms the central contribution of this paper.

We show that dividend growth is predictable when consideration of managerial discretion in setting dividend policy is taken into account, something that has been ignored in standard return decompositions. Based on a dividend smoothing model, dividends are paid as a function of (i) earnings, which reflect the current position of the firms cash flows and, potentially, any asymmetric information between managers and shareholders, and (ii) stock prices, which proxy expected future earnings. Consistent with this, in the data there is a long-run relation between dividends, earnings and prices, that is, they are cointegrated. This relation predicts dividend growth and has both time series and cross sectional implications for the analysis of stock price movements which help us to answer the questions posed above.

We find that deviations from the long-run trend of dividends, earnings and prices (which we refer to as *dpe*) are able to predict dividend growth over the period 1927 to 2009. The \bar{R}^2 is 37% at both the one and two year horizons, steadily falling to 18% at the five year horizon.³ According to the \bar{R}^2 , the extent of dividend growth predictability that we uncover is much stronger than that of the stock return predictability that has been reported in the literature. Further, we also find that when we use *dpe* to predict dividend growth, the predictability is not confined to the pre-war period. This is in contrast to the results in Chen (2009), where the ability of the dividend-price ratio to predict dividend growth disappears in the post-war period.⁴

To understand the role cash flow news plays in the time series of returns, we examine its contribution to explaining the variance of unexpected returns and find that when cash flow news is estimated directly by exploiting the predictability of dividend growth we identify, the covariance of cash flow news with returns increases, often quite substantially, compared to when cash flow news is backed out of the return decomposition. Following Campbell and Ammer

³A Monte Carlo experiment shows that the predictability of dividend growth is not driven by the small sample problems that usually affect predictive regressions.

⁴Chen, Da and Priestley (2010) show that this is related to dividend smoothing.

(1993), we also examine the R^2 s from a regression of unexpected returns on cash flow news and find that when cash flow news is estimated directly the R^2 increases. For example, when we estimate cash flow news directly the R^2 is 43.5% as compared to 27.6% when cash flow news is backed out of the return decomposition from the Campbell and Vuolteenaho (2004) return VAR. Moreover, our results indicate that irrespective of the variables used to predict returns, the correlation between unexpected returns and cash flow news is always higher when we directly estimate cash flow news.

These two findings indicate that, contrary to the extant literature, dividend growth is predictable and when we exploit this predictability, cash flow news becomes relatively more important in explaining stock price movements. An interesting follow-on question is whether these time series findings have any implications for the cross-section of returns. To investigate this, we consider separate VARs to estimate discount rate betas and cash flow betas. In this case, Chen and Zhao (2009) show that the market beta will equal the discount rate beta plus the cash flow beta plus the beta that arises from the unmodeled residual, which Chen and Zhao (2009) term the noise beta. We find that cash flow betas calculated from directly estimated cash flow news are substantially larger than those from when cash flow news is backed out of the return decomposition. Our results also suggest that cash flow betas provide a spread that is consistent with the size effect but that the spread across value and growth portfolios, which is a central feature of Campbell and Vuolteenaho (2004), vanishes. However, we do find that the noise betas have a reasonable spread across value and growth portfolios.⁵

We examine whether differences in the betas from different VARs matter empirically by assessing their ability to explain the cross section of returns. When we use the directly estimated cash flow and discount rate betas and include the noise beta, the results indicate that it is the cash flow and noise components that seem to be more important in explaining the cross section of returns. This appears to be the case irrespective of the instruments we choose to forecast stock returns. The estimated price of risk for the cash flow beta is in the region of 30% per

⁵Given the findings in Chen and Zhao (2009), we also examine the impact of alternative instruments for forecasting stock returns on the estimation of discount rate betas and noise betas. The results are consistent with our main findings, irrespective of the return forecasting instruments.

annum for four of the different specifications of the return VAR that we consider, and around 17% per annum for the remaining two. The price of risk associated with the noise beta, however, ranges from 2.4% per annum to 35% per annum, depending on the specification of the return forecasting VAR. The estimate of the price of risk on the discount rate beta, when positive, ranges between 5% and 15%. Unfortunately, it is negative in three of the cases we consider, making inferences about the coefficient of relative risk aversion (given as the ratio of the cash flow price of risk to the discount rate price of risk) in the context of Campbell and Vuolteenaho's (2004) version of Campbell's (1993) ICAPM challenging.

The cash flow and noise prices of risk typically contribute around half of the explanatory power in the cross section, with most of the models generally performing as well as the Campbell and Vuolteenaho (2004) model in terms of the cross-sectional \bar{R}^2 and pricing error. However, using directly-estimated cash flow news rather than cash flow news backed out of a return-forecasting VAR generates results that suggest a different interpretation to the findings in Campbell and Vuolteenaho (2004). They find that cash flow betas based on backing out cash flow news from the return decomposition explain the value spread. Our results suggest that when we estimate cash flow news directly from our model of dividend growth predictability, cash flow betas exhibit a spread across size rather than value, with noise betas exhibiting a spread across value.

The conclusion from our analysis is that cash flow news estimated directly from a regression predicting dividend growth assumes a more important role in determining the cross section of returns than when it is backed out as a residual from the return decomposition. This finding is consistent with our earlier evidence that dividend growth is more predictable than returns, as well as the results in Larrain and Yogo (2008), who find that movements in the net payout ratio are driven by movements in expected cash flow growth and not movements in discount rates, and the results in Chen and Zhao (2010) who find an important role for cash flow news when cash flow news is derived from earnings forecasts.

A final issue we consider is the role of cash flow and discount rate news in recent equity market movements. Campbell, Giglio and Polk (2010) estimate both unrestricted VARs and a restricted

model that imposes ICAPM restrictions to understand the impact of discount rate news and cash flow news on the boom-bust cycles of the late 1990s and early 2000s in particular. Campbell, Giglio and Polk (2010) follow Campbell and Vuolteenaho (2004) by estimating discount rate news and backing out cash flow news as a residual from the return decomposition. They find that the technology boom and bust in the late 1990s/early 2000s was driven primarily by discount rate news while the downturn in the late 2000s is driven by cash flow news.

Estimating cash flow news directly from our dividend growth VAR rather than backing it out of the return decomposition once the return VAR has been estimated, we find that cash flow news also has an important role in the stock price increase throughout the 1990s and the subsequent fall in prices over 2000–2002. Consistent with Campbell, Giglio and Polk (2010), we also find that cash flow news was important for the price increases in the mid 2000s and the following collapse in prices in 2007–2008. These findings further illustrate the potential importance of directly estimating cash flows news if one wants to fully understand the causes of stock price movements.

In sum, our paper contributes to the literature by showing, first, that dividend growth is predictable using a novel variable based on the dividend-smoothing behavior of managers. The time series results show that, relatively, dividend growth is more predictable than returns and that when we exploit this predictability, the relative contribution of cash flow news to return variability increases. This is an interesting finding given the view that 100% of the variation in prices is driven by directly measured discount rate news (Cochrane (2010)). Second, dividend growth predictability has an impact on the cross-sectional implications of the return decomposition. Campbell and Vuolteenaho's (2004) results when backing out cash flow news have become influential since they find that cash flow beta can explain the value-growth spread (see also Campbell, Polk and Vuolteenaho (2010)). In cross-sectional regressions where return predictability and cash flow predictability are assessed separately, we find that the discount rate beta is not as important in explaining the cross-sectional variation in returns. In contrast, the cash flow betas, which appear to capture the size effect, and noise betas, which appear to capture the value effect, do seem capable of explaining the cross section of stock returns. Finally,

we illustrate the potential importance of directly estimating cash flow news on interpreting the causes of recent stock market movements.

The rest of the paper is organized as follows. Section two presents a model of dividend behavior that motivates our choice of predictor variable for dividend growth. Section three focuses on predicting dividend growth and provides an analysis of the contribution of cash flow news to the time-series variation in stock prices. In Section four, we focus on the cross section of returns. Section five examines the role of cash flow news on recent stock market movements. Section six offers concluding remarks.

II. A Model Of Dividend Growth

In this section of the paper, we motivate the predictability of dividend growth using a new predictor variable that has its roots in the corporate finance literature on the dividend behavior of firms. In his seminal paper, Lintner (1956) finds that there is a long-run target dividend payout ratio to which managers adjust actual dividends gradually, that managers will change dividends in response to a permanent change in earnings, and that managers are reluctant to make dividend changes that will have to be reversed at a later date. Below, we outline the source of predictability of dividend growth based on the model of dividend behavior in Garrett and Priestley (2000) which has its roots in Lintner’s insights. Consider the following cost function:

$$(1) \quad C = \theta_1(d_t - d_t^*)^2 + \theta_2(\Delta d_t - \alpha)^2,$$

where d is the log dividend, d^* is the target log dividend, α is some ‘normal’ level of dividend growth and θ_1 and θ_2 are parameters. The second term represents the costs incurred when dividend growth differs from the ‘normal’ level. Given that managers are reluctant to make dividend changes that later have to be reversed, excessive growth in dividends can be just as costly as insufficient growth in dividends. The costs associated with deviations of dividend growth from the norm are therefore quadratic. The first term reflects costs associated with the actual dividend deviating from the target dividend. Differentiating (1) with respect to d_t and

solving gives

$$(2) \quad \Delta d_t = \left(\frac{\theta_2}{\theta_1 + \theta_2} \right) \alpha + \left(\frac{\theta_1}{\theta_1 + \theta_2} \right) (d_t^* - d_{t-1})$$

This is Lintner's (1956) seminal partial adjustment model written as a model of dividend growth. Equation (2) is widely used in empirical work, with d^* typically specified as a function of earnings, and seems to work reasonably well (see among many others Fama and Babiak (1968) and Dewenter and Warther (1998)). However, it has an unattractive feature theoretically. Since (1) implies (2), Lintner's partial adjustment model implies that managers are penalized by the same amount irrespective of whether they move towards or away from the target dividend. In other words, the costs of being away from the target dividend are not offset at all if managers set dividends so as to move towards the target. This seems unreasonable. To overcome this problem, Garrett and Priestley (2000) propose the following:

$$(3) \quad C = \theta_1(d_t - d_t^*)^2 + \theta_2(\Delta d_t - \alpha)^2 - 2\theta_3(d_t - d_{t-1})(d_t^* - d_{t-1}^*)$$

The last term in (3) captures the proposition that if the actual dividend moves nearer to the target dividend, the costs of being away from the target will be offset by the fact that at least dividends are moving in the right direction. Differentiating (3) with respect to d_t and solving leads to the following model of dividend growth:

$$(4) \quad \Delta d_t = \left(1 - \frac{\theta_1}{\theta_1 + \theta_2} \right) \alpha + \left(\frac{\theta_1 + \theta_3}{\theta_1 + \theta_2} \right) \Delta d_t^* - \left(\frac{\theta_1}{\theta_1 + \theta_2} \right) (d_{t-1} - d_{t-1}^*)$$

This is an error correction model of dividend behavior that incorporates Lintner's (1956) model as a special case. The last term in (4) represents the deviation of target and actual dividends from their common trend and is a cointegrating vector. $\left(\frac{\theta_1}{\theta_1 + \theta_2} \right)$ is the speed at which dividends will change in response to a deviation of actual and target dividends from their common trend. The greater is the cost associated with being away from the target dividend, the faster will be the speed of adjustment to the target.

To convert (4) into an empirically operational model of dividend growth, the target dividend needs to be specified. As managers will increase dividends in response to an increase in permanent earnings, a natural specification of the target is as some function of permanent earnings. Since permanent earnings are not observable, many studies follow Lintner and specify the target as a function of observed earnings. The survey evidence in Brav, Graham, Harvey and Michaely (2005) shows that earnings still affect dividends, although the relationship has weakened. This establishes the link between dividends and earnings in the long run.

In addition, given that managers are reluctant to decrease dividends, a dividend payment today reflects information about future permanent earnings. Therefore, as an alternative, Marsh and Merton (1987) suggest that in ‘reasonably efficient’ markets, stock prices should provide a (noisy) forecast of future permanent earnings and therefore the target dividend will also be related to the stock price.

Garrett and Priestley (2000) generalize both Lintner (1956) and Marsh and Merton (1987) by specifying target dividend growth and target dividends as a function of both permanent earnings and stock prices. There are good reasons for specifying the target dividend and target dividend growth in this way. First, if there is information asymmetry between managers and investors, then an unexpected change in permanent earnings that is known by managers, but is not yet known by the market, can be conveyed to the market via changes in dividends. This is not inconsistent with the model in Miller and Rock (1985), for example, and the evidence in Benartzi, Michaely and Thaler (1997) that dividends convey information about current earnings. Second, Garrett and Priestley (2000) find that (4) with d_t^* as a function of stock prices and earnings performs substantially better than both Lintner’s and Marsh and Merton’s models and that there is strong evidence in favor of a long-run relationship between dividends, earnings and prices, that is, they are cointegrated.

There is a further link from dividends to earnings and prices. Jagannathan, Stephens and Weisbach (2000) document that stock repurchases are pro-cyclical, with firms repurchasing stock following poor stock market performance and increasing dividends following good performance. Grullon and Michaely (2002) go so far as to suggest that firms substitute repurchases for div-

idends, although the survey evidence in Brav, Graham, Harvey and Michaely (2005) does not support this. Brav, Graham, Harvey and Michaely (2005) do document that managers attempt to time the market by using repurchases when the stock price is low. This suggests that dividends depend not only on earnings but on stock price as well if dividends and repurchases are substitutes. We therefore specify the target as a function of both stock prices and permanent earnings. The error correction term that we use in (4), which we label dpe , is therefore

$$(5) \quad dpe_t = d_t - \beta_0 - \beta_1 p_t - \beta_2 e_t^*$$

where e_t^* is log permanent earnings. The empirical counterpart to (4) then becomes

$$(6) \quad \Delta d_t = \alpha_0 + \alpha_1 \Delta p_t + \alpha_2 \Delta e_t^* + \alpha_3 dpe_{t-1} + \epsilon_t$$

where Δp_t is the capital gain, Δe_t^* is the shock to permanent earnings and u_t is an error term.⁶ As it stands, (6) is not operational as a forecasting equation as it involves contemporaneous variables on the right hand side. However, since Δe_t^* is the shock to permanent earnings in this model, $E_t(\Delta e_{t+k}^*)$ is zero (or a constant if log permanent earnings are a random walk with drift.) Likewise, since log stock prices are well approximated by a random walk, $E_t(\Delta p_{t+k}) = 0$. These terms therefore drop out when using (6) to forecast dividend growth. This leaves us with the predictive regression

$$(7) \quad \Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + u_{t+k}.$$

We examine the ability of this model to predict dividend growth in the next section.

⁶As in Lintner (1956), Fama and Blahnik (1968) and Dewenter and Warther (1998) we proxy e_t^* with actual earnings in our empirical tests.

III. Time Series Analysis

In this section, we first test for cointegration between dividends, earnings and prices, an essential precursor to any predictability tests we consider using dpe . Having established the existence of cointegration, we present results of dividend growth predictability using dpe . Given this predictability, we provide further evidence on the role of cash flow news in determining stock price movements by examining various VARs that provide estimates of cash flow news and discount rate news which we can compare to return shocks in order to assess how important the news terms are.

A. Cointegration

We use annual end-of-year data on the level of the S&P 500 Index, and dividends and earnings for the S&P 500 from 1927 to 2009. We deflate prices, dividends and earnings by the Consumer Price Index.⁷ Let d_t, p_t and e_t be log real dividends, log real prices and log real earnings respectively.

In unreported results, and consistent with the extant literature, there is no evidence that either the dividend-price ratio or the dividend-earnings ratio can predict dividend growth. Predictability by either of these two ratios would imply that there are two cointegrating vectors between dividends, earnings and prices. The model of dividend behavior outlined in section II implies only one cointegrating vector between the three variables. It is straightforward to test these relations.

We test for cointegration between dividends, earnings and prices using the Engle and Granger (1987) methodology. The Engle and Granger Cointegrating Regression Durbin-Watson test rejects the null hypothesis of a unit root in the residuals from the cointegrating regression of dividends on a constant, prices and earnings, indicating that dividends, prices and earnings are cointegrated. The test statistic is 0.97 and statistically significant at the 1% level. The Augmented Dickey-Fuller test also rejects the null of a unit root in the residuals with a test

⁷We are grateful to both Robert Shiller and Amit Goyal for making this data available. It can be downloaded from Shiller's website at <http://www.econ.yale.edu/~shiller/data.htm> and Goyal's website at <http://www.bus.emory.edu/AGoyal/>.

statistic of -5.01 which is statistically significant at the 1% level. The estimated cointegrating vector is $dpe_t = d_t + 2.332 - 0.260p_t - 0.256e_t$. The first order autocorrelation coefficient of dpe is 0.51, showing that it is substantially less persistent than the dividend-price ratio, for example, which has a first order autocorrelation coefficient of 0.88. This is an important point when dealing with predictive regressions since it is well known that their small sample properties are affected by the persistence of the forecasting variable.

As the Engle-Granger method assumes there is one cointegrating vector, we also used the Johansen method to test for the number of cointegrating vectors between dividends, prices and earnings (see Johansen and Juselius (1990)). Testing the null hypothesis that there are zero cointegrating vectors delivers a λ_{Trace} test statistic of 42.70, which is significant at the 1% level. The corresponding statistic testing the null hypothesis that there is one cointegrating vector is 13.67, which is insignificant at the 5% level. This suggests that there is one cointegrating vector between dividends, prices and earnings, consistent with the evidence in Garrett and Priestley (2000).

B. Dividend Growth Predictability with dpe

We now turn to examining the predictability of dividend growth with dpe . Table 1 reports results from estimating (7) over different forecasting horizons. The left hand side panel of Table 1 presents results using the full sample. At the one year horizon dpe is highly statistically significant, has the correct sign and the \bar{R}^2 is an impressive 37%. In terms of economic impact, a one standard deviation change in dpe ($\sigma_{dpe} = 0.14$) results in a 7% change in dividend growth. The results contrast sharply with those in the extant literature that use the dividend-price and dividend-earnings ratios to predict dividend growth, and indicate that a substantial proportion of dividend growth is predictable on an annual basis.

Looking at longer horizons, Table 1 shows that the extent of predictability remains at 37% at the two year horizon. At subsequent horizons both the size of the coefficients and their statistical significance start to fall, although using conventional critical values, dpe is a statistically significant predictor of dividend growth at all the horizons considered and in terms of \bar{R}^2 the

Insert

Table 1

about

here

predictability appears to be economically important, though its predictive power declines as the horizon increases.⁸

This predictability suggests that there is an avenue for news regarding cash flows to have a more substantive impact on stock price movements than has previously been suggested in the literature. One possible way of assessing the importance of cash flow and discount rate news in stock prices is to assess the relative predictability of dividend growth and returns. We will not reproduce extensively reported results on stock return predictability, but a brief peruse of the literature indicates that stock return predictability is certainly weaker than the dividend growth predictability reported here.⁹ Therefore, based on the metric of predictive power as measured by the \overline{R}^2 , cash flow news is an important driver of price movements.

One particularly interesting finding is that of Chen (2009) who shows that dividend growth is predictable using the dividend price ratio in the pre-war period but not so in the post-war period. A potential explanation for this finding is outlined in Chen, Da and Priestley (2010) who show that it is driven by the increase in dividend smoothing, as measured using the Lintner (1956) and Marsh and Merton (1987) models, in the post-war period. These models of dividend smoothing use either earnings or prices, but not both together in the form used here. There is also evidence (Lettau and Van Nieuwerburgh (2008)) that the log dividend-price ratio exhibits structural breaks in the post-war period; *dpe* is stable.¹⁰

In the right hand side panel of Table 1, we assess the ability of *dpe* to predict dividend

⁸A Monte Carlo experiment that assesses the small sample properties of the Newey-West *t*-statistics reveals that the predictability we uncover using conventional critical values for the *t*-statistics remains. For example, the 5% left tail critical values for the Newey-West *t*-statistics generated from the Monte Carlo experiments are -1.76 , -2.00 , -2.09 , -2.15 , and -2.19 at the 1, 2, 3, 4, and 5 year horizon respectively. These are all considerably larger than the *t* statistics reported in Table 1. Details of the Monte Carlo experiment can be found in the online appendix.

⁹For example, one of the most successful predictors of stock returns is Lettau and Ludvigson (2001)'s *cay*. They report an \overline{R}^2 of 14% when forecasting returns at an annual horizon. Many other predictors of stock returns have weaker forecasting power, see Goyal and Welch (2008).

¹⁰Results available in the online appendix show that the estimated cointegrating relationship is stable according to the Hansen (1992) and Andrews (1993) tests.

growth in the post-war period. At the one year horizon, we find that dpe has predictive power for dividend growth. The estimated coefficient is -0.266 with an associated t -statistic of -2.48 and an \bar{R}^2 of 23%. Although the \bar{R}^2 falls a little for the two and three year horizons, dpe still has predictive power. Both the coefficient estimates and the \bar{R}^2 s increase for the longer forecasting horizons. Therefore, the ability of dpe to predict dividend growth is also observable in the post-war sample, a result that contrasts with the findings of Chen (2009) in relation to the dividend-price ratio.

C. Cash Flow News and Time Variation in Stock Prices

We now turn to estimating various VARs that predict dividend growth and stock returns and look at how much of the variance of unexpected returns is due to cash flow news and how much is due to discount rate news. This method has a long history in assessing the contribution of discount rate and cash flow news to movements in stock returns (see, for example, Campbell (1991), Campbell and Ammer (1993), Vuolteenaho (2002) and Chen and Zhao (2009)). Consider Campbell's (1991) decomposition of unexpected returns from the present value model:

$$\begin{aligned}
 (8) \quad r_{t+1} - E_t(r_{t+1}) &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho^i r_{t+1+i} \\
 &= N_{CF,t+1} - N_{DR,t+1}
 \end{aligned}$$

where N_{CF} and N_{DR} are news about future dividend growth (cash flows) and future returns (discount rates) respectively. To implement (8) Campbell and Vuolteenaho (2004) follow Campbell (1991) and estimate a VAR to obtain $E_t(r_{t+1})$ and $(E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho^i r_{t+1+i}$. These are then plugged into (8), which can then be solved for $(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$. Assuming the data are generated by a first order VAR:

$$(9) \quad \mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{u}_t$$

then Campbell and Vuolteenaho (2004) show that the news terms are given by

$$(10) \quad \begin{aligned} N_{CF,t} &= (\mathbf{e}'_1 + \mathbf{e}'_1 \boldsymbol{\lambda}) \mathbf{u}_t \\ N_{DR,t} &= \mathbf{e}'_1 \boldsymbol{\lambda} \mathbf{u}_t \end{aligned}$$

where \mathbf{e}_1 is a vector that picks out the first element from \mathbf{z}_t , which is excess returns in Campbell and Vuolteenaho (2004), and $\boldsymbol{\lambda} = \rho \mathbf{A} (\mathbf{I} - \rho \mathbf{A})^{-1}$.

To understand the contribution of cash flow and discount rate news to stock price fluctuations, we follow Chen, Da and Larrain (2010) and decompose the variance of returns as follows:

$$(11) \quad Var(u_{r,t+1}) = Cov(u_{r,t+1}, -N_{DR,t+1}) + Cov(u_{r,t+1}, N_{CF,t+1})$$

where $Var(u_{r,t+1})$ is the variance of unexpected returns. Dividing both sides of (11) by $Var(u_{r,t+1})$ enables us to calculate the proportion of the variation in unexpected returns that is due to each of the news terms. In addition to the variance decomposition, following Campbell and Ammer (1993), we also report the R^2 statistic from a regression of unexpected returns on each of the components separately in order to assess the individual contribution of each component to unexpected returns. Note that if the terms on the left hand side of (11) are correlated, the R^2 statistics need not sum to one.

Insert

To investigate the impact of being able to predict dividend growth on estimates of cash flow and discount rate news, we begin by considering two VARs. In the first VAR, we predict real S&P returns using the same predictor variables that Campbell and Vuolteenaho (2004) use. These are the term yield spread, TY , the 10-year price-earnings ratio, $PE10$, the small-stock value spread, VS , and lagged returns, r .¹¹ For the first VAR, then, $\mathbf{z}'_t = [r_t \quad TY_t \quad PE10_t \quad VS_t]$. In the second VAR, we model dividend growth using dpe_t and, following Chen and Zhao (2009), returns. Parameter estimates for both of these VARs are presented in Table 2. Panel A reports

Table 2

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¹¹ TY is measured as the yield difference between 10-year constant-maturity taxable bonds and short-term taxable notes, $PE10$ is the log of the ratio of the S&P 500 price to a 10-year moving average of S&P 500 earnings and VS is the difference in the log book-to-market ratios of small value and small growth stocks. We are grateful to Tuomo Vuolteenaho for making these variables available on his Harvard website.

results for $\mathbf{z}'_t = [r_t \quad TY_t \quad PE10_t \quad VS_t]$ while Panel B reports results for $\mathbf{z}'_t = [\Delta d_t \quad r_t \quad dpe_t]$. From Panel A, there is some evidence that real returns are predictable: the R^2 is 7%, with the PE ratio being significant at the 1% level. The value spread also has some marginal predictive power at the 10% level. TY appears to have no predictive power. The results in Panel B show that real returns and dpe seem to do a very good job of predicting dividend growth with the \bar{R}^2 being an impressive 46%.

In Panel C of table 2, we report the variance decomposition of unexpected returns.¹² Taking the Campbell-Vuolteenaho VAR as a reference point, the covariance of the negative of discount rate news with returns is somewhat larger than that of cash flow news, indicating that around 78% of the variation in unexpected returns is due to its covariance with discount rate news. This large role for discount rate news is also reflected in the R^2 s from regressions of unexpected returns on the news terms which are 82% for discount rates and 28% for cash flow news. This indicates that when cash flow news is not measured directly, discount rate news is the predominant driver of return variability.¹³

When predicting dividend growth, and hence estimating cash flow news directly, and backing out discount rate news as the residual from the return decomposition, the importance of cash flow news increases somewhat relative to that for the Campbell-Vuolteenaho VAR. The results suggest that when we estimate cash flow news directly, a third of the variance in unexpected returns is due to its covariance with cash flow news. This is an increase in covariance between unexpected

¹²We follow Campbell and Vuolteenaho (2004) and set $\rho = 0.95$ when calculating λ in (10). Campbell and Shiller (1988), Campbell and Vuolteenaho (2004) and Chen and Zhao (2009) find that for reasonable choices of ρ (usually between 0.90 and 0.95), the results are robust.

¹³Chen and Zhao (2009) show that the estimation of discount rate news is highly sensitive to the choice of instruments that are used to predict returns. We confirm these findings in results available in the online appendix that employ different VARs for forecasting returns and back out cash flow news as the residual. The proportion of unexpected return variance that is due to covariance with cash flow news and discount rate news changes given the specification of the returns VAR. The R^2 s from the regression of unexpected returns on discount rate news range from 46% to 85%. The R^2 s from the regression of unexpected returns on backed-out cash flow news range from 11% to 68%. These findings about the sensitivity of the results to different return-forecasting instruments are consistent with those in Chen and Zhao (2009).

returns and cash flow news of some 54% relative to that for the Campbell-Vuolteenaho VAR. This has a big impact on the R^2 from the regression of unexpected returns on the cash flow news term which rises to 57%. Thus, exploiting the predictability of dividend growth that we document earlier in the paper, it appears that cash flow news becomes more important than in the Campbell-Vuolteenaho VAR, where cash flow news is backed out of the return decomposition as a residual.

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The results in Table 2 either ignore dividend growth predictability or return predictability. In Table 3, we report the variance decomposition for returns under different specifications of the VAR for stock returns but with the same VAR for dividend growth. The first return VAR is the base-case Campbell-Vuolteenaho VAR. The second VAR drops the insignificant term yield (TY) such that \mathbf{z}_t contains returns, the price-earnings ratio and the value spread; the next three VARs add the book-to-market ratio, the equity share in new issues and both the book-to-market ratio and the equity share in new issues. Finally, following the finding in Chen and Zhao (2009) that the results are sensitive to the inclusion of the 10-year PE ratio in the return forecasting VAR, we revisit the Campbell-Vuolteenaho VAR but replace the 10-year PE ratio first with a one-year PE ratio and second with the dividend-price ratio.

Table 3

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As we are now directly estimating both discount rate and cash flow news, the two sources of news may not add up to the unexpected return, that is, (8) need not hold. Estimating discount rate and cash flow news directly leaves a further news item: unmodeled news, which Chen and Zhao (2009) label noise news. This is given by the return shock net of estimated discount rate news and cash flow news. The variance decomposition now becomes

$$(12) \quad Var(u_{r,t+1}) = Cov(u_{r,t+1}, -N_{DR,t+1}) + Cov(u_{r,t+1}, N_{CF,t+1}) + Cov(u_{r,t+1}, N_{NOISE,t+1}).$$

The covariance of cash flow news with the unexpected return accounts for around 30% of the variance of unexpected returns and the covariance of discount rate news accounts for around 75%. The covariance with noise news accounts for only a very small proportion of the unexpected return variance. What is also worthy of note is the finding that the R^2 s from the regression

of unexpected returns on cash flow news are fairly constant across all specifications of the return VAR, ranging from 35% to 47%, indicating a strong and stable role for cash flow news in explaining the variability of stock returns. In contrast, our results indicate that the role of discount rate news varies considerably across different specifications of the VAR, with R^2 s ranging from 46% to 85%. The results also lend support to the findings in Chen and Zhao (2009) concerning the sensitivity of the return VAR to the inclusion of the 10-year PE ratio. In particular, the 10-year PE ratio is responsible for a large part of the predictability of returns and hence the contribution of discount rate news to unexpected return variance. This is particularly evident when we replace the ten-year PE ratio with the log dividend-price ratio. For example, comparing rows one and seven in Table 3, where we use the ten-year PE ratio in the former and the dividend-price ratio in latter, the contribution of discount rate news to the unexpected return variance decreases quite dramatically, as can be seen by the R^2 falling from 82% to 55%. The contributions of both cash flow and noise news, on the other hand, increase.

Overall, the results indicate that once we have a reliable predictor of dividend growth, it would seem that cash flow news is an important determinant of stock price variation through time, as evidenced by the increase in the relative contribution of cash flow news in explaining the variance of unexpected returns, a contribution that seems to remain stable irrespective of the predictor variables included in the return VAR.

Due to the inability of the dividend-price ratio to predict dividend growth, much of the extant literature has concluded that only discount rate news is important with respect to the time-series variation in prices. Taking account of managerial discretion in paying dividends, we model dividend growth as the long-run relation between dividends, earnings and prices and find substantial and stable predictability of dividend growth. It transpires that when we exploit this predictability there appears to be a more substantial role for cash flow news in stock price fluctuations than has been uncovered previously. In the next section of the paper, we examine the implications of directly measuring cash flow news on the cross-section of returns.

IV. Cross-Sectional Analysis

There is a growing interest in measuring cash flow risk when assessing the cross-sectional differences in expected stock returns. Campbell and Vuolteenaho (2004) find that value stocks have relatively large cash flow betas and growth stocks have relatively large discount rate betas. Theoretically, Campbell (1993) shows that the cash flow betas carry a risk premium that is γ times that commanded by the discount rate beta, where γ is the coefficient of relative risk aversion. Therefore, measuring the spread in cash flow and discount rate betas provides a first step in assessing the ability of these betas to explain the cross section of returns. The second step is to examine the prices of risk associated with the cash flow and discount rate betas because Campbell and Vuolteenaho (2004) show that, even though the standard CAPM beta for value stocks is lower than for growth stocks it is the fact that, theoretically, when the market beta is decomposed, the cash flow beta earns a higher price of risk than the discount rate beta and it is this that could explain the value effect. However, one needs to estimate the prices of risk in order to ascertain this.

A. Estimating Betas

Armed with estimates of discount rate and cash flow news, the cash flow β for asset i can be estimated as (Campbell and Vuolteenaho (2004))

$$(13) \quad \hat{\beta}_{i,CF} = \frac{\widehat{\text{Cov}}(r_{i,t}, \hat{N}_{CF,t})}{\widehat{\text{Var}}(\hat{N}_{CF,t} - \hat{N}_{DR,t})}$$

where the term in the denominator is the variance of unexpected market returns. The estimated discount rate β is

$$(14) \quad \hat{\beta}_{i,DR} = \frac{\widehat{\text{Cov}}(r_{i,t}, -\hat{N}_{DR,t})}{\widehat{\text{Var}}(\hat{N}_{CF,t} - \hat{N}_{DR,t})}$$

The market beta is given by the sum of the discount rate and cash flow betas.

Table 4 documents estimated cash flow and discount rate betas for the Fama-French 25 size

and book-to-market portfolios. As a point of reference, Panel A reports betas from the VAR using the Campbell-Vuolteenaho predictor variables that estimates discount rate news and then backs out the cash flow news as a plug. Similar to Campbell and Vuolteenaho (2004), we find that the cash flow betas are higher for value stocks than for growth stocks and that the spread in cash flow betas across value and growth stocks is statistically significant.¹⁴ The variability in the magnitude of the cash flow betas is smaller across size than across book-to-market. For example, the difference across growth and value stocks is just over 0.2 irrespective of size. The difference across size portfolios is less than 0.1 and changes between positive and negative. The opposite pattern is evident in the discount rate betas where the betas are higher for growth stocks than for value stocks, but the variation is greater across size than across book-to-market. In sum, according to the Campbell and Vuolteenaho (2004) decomposition, cash flow betas appear to pick up the variation in returns across value and discount rate betas appear to pick up variation across size.

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In Panel B, we report estimates of cash flow, discount rate and noise betas. As in Panel A, the discount rate betas are estimated directly from the Campbell and Vuolteenaho (2004) VAR. The cash flow betas are estimated from the dividend growth VAR, and the noise betas from the difference between these two news terms and the return shock from the Campbell-Vuolteenaho VAR. Three patterns in the betas are worthy of note. First, the cash flow betas increase considerably, often by a magnitude of two to three times. Second, when we estimate cash flow news directly from our model the cash flow betas lose their spread across value and growth stocks in all but the next to largest size quintile. Therefore, the pattern in the cash

Table 4
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¹⁴To assess the statistical significance of the difference in the betas in the extreme cells, we follow Campbell and Vuolteenaho (2004) and Chen and Zhao (2009) by bootstrapping the standard errors of the differences. This is necessary because the numerator in (13) and (14) is not the usual numerator that appears in the familiar formula for the CAPM beta. We begin by estimating the VAR using the original data. We then simulate each variable in the system using the coefficients from the VAR estimated using the original data and bootstrapping the shocks. We then re-estimate the VAR and use the newly estimated coefficients to estimate the betas. We repeat this 10,000 times, giving 10,000 of each beta and therefore 10,000 differences from which we can calculate the standard error and hence a bootstrapped t statistic.

flow betas we find does not appear to be consistent with the value effect in stock returns. We find there is a more pronounced spread across size where the results show that the difference in cash flow betas for the small and large stock portfolios are negative and statistically significant. Third, we find that there is a large and statistically significant cross-sectional spread in the noise betas across value and growth portfolios, but not so much across size portfolios. These findings indicate that once we use an estimate of cash flow news that comes from our regression that predicts dividend growth, cash flow betas are larger and give a reasonable spread across size portfolios while noise betas give a spread across value portfolios.¹⁵

The main results that emerge thus far in relation to discount rate and cash flow betas can be summarized as follows. First, when we exploit the predictability of dividend growth that we identify in section three to directly estimate cash flow news, cash flow betas increase, sometimes dramatically, across all portfolios. Second, cash flow betas appear to lose their spread across value and growth, though they still provide a spread across size, and third, noise betas have a spread across value and growth. Our results indicate that when cash flow news is directly estimated from our model, it is not cash flow betas that give a spread across value and growth. They do give on average higher betas and hence expected returns, but the spread across value and growth is determined by the noise betas.

Having established that directly estimating cash flow news gives a different picture to the pattern in betas across portfolios, at least when using our model to predict dividend growth, we now turn to examining whether this affects the ability of these betas to explain the cross-section of returns by estimating their respective prices of risk.

¹⁵We also examined whether the estimated betas are sensitive to the specification of the return forecasting VAR by repeating the analysis for the return predictor information sets examined in Table 3. The results appear quite robust to the specification of the return forecasting VAR, with cash flow betas only providing a spread across size while noise betas tend to provide a spread across value and growth. To conserve space, these results are available in an online appendix.

B. Estimating Prices of Risk

The test assets we use are the Fama-French 25 size and book-to-market-sorted portfolios and the 20 RISK portfolios used by Campbell and Vuolteenaho (2004). We consider several different sets of cross-sectional regression results, all of which are reported in Table 5. The first is to provide a reference point and uses a restricted version of the Campbell-Vuolteenaho VAR to predict returns, thereby estimating the return shock and discount rate news.¹⁶ From (8), cash flow news is then calculated as the difference between the return shock and the estimated discount rate news. These are then used as inputs to calculate the respective betas to be used in the following cross-sectional regression:

$$(15) \quad R_i - R_f = \lambda_0 + \lambda_{DR}\widehat{\beta}_{DR} + \lambda_{CF}\widehat{\beta}_{CF} + \epsilon_i$$

where $R_i - R_f$ is the average excess return on test asset i , λ_{DR} is the price of risk associated with discount rate news, λ_{CF} is the price of risk associated with cash flow news and ϵ_i is the residual. In this specification, Campbell and Vuolteenaho (2004) show that the coefficient of relative risk aversion is given as the ratio of λ_{CF} to λ_{DR} .

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The second cross sectional regression uses the discount rate betas estimated from the Campbell-Vuolteenaho VAR, as in the first cross sectional regression. However, the cash flow betas are estimated directly from cash flow news estimated from the VAR predicting dividend growth. This requires that the first cross sectional regression be supplemented with a term capturing the price of risk relating to the noise betas, that is,

Table 5

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$$(16) \quad R_i - R_f = \lambda_0 + \lambda_{DR}\widehat{\beta}_{DR} + \lambda_{CF}\widehat{\beta}_{CF} + \lambda_{NOISE}\widehat{\beta}_{NOISE} + \epsilon_i$$

Table 5 also reports an \overline{R}^2 for each regression and, following Campbell and Vuolteenaho (2004)

¹⁶The results in Panel A of Table 2 show that the term yield, TY , is not significant in the VAR predicting returns. We therefore drop TY from the VAR. The effect this has on the estimated betas from the previous section is negligible: the spread across betas remains essentially unaltered both quantitatively and qualitatively when moving from $\mathbf{z}'_t = [r_t \quad TY_t \quad PE10_t \quad VS_t]$ to $\mathbf{z}'_t = [r_t \quad PE10_t \quad VS_t]$.

a return-volatility-weighted squared pricing error, calculated as either $\epsilon' \Sigma^{-1} \epsilon$ or $\epsilon' \Sigma^{-1} \epsilon$, where Σ is a diagonal matrix where the i th diagonal element is the estimated return volatility for asset i .

Panel A of Table 5 contains the results from the first cross-sectional regression (15) and shows that the Campbell-Vuolteenaho VAR, which predicts returns and calculates cash flow news as a plug, appears to do a good job of explaining the cross-section considered here. The prices of risk on both the cash flow and discount rate betas are significant and positive, the explanatory power of the cross-sectional regression is some 65% and the model delivers an estimated coefficient of risk aversion, calculated as the ratio of the cash flow price of risk to the discount rate price of risk, of around 5.4, which seems reasonable. It is also important to note that the price of risk associated with cash flow risk of 31% per annum, coupled with the pattern in cash flow betas backed out of the Campbell and Vuolteenaho (2004) decomposition discussed in the previous subsection, matches the high average return of the value portfolios.

Panel B reports the results from the model with directly estimated discount rate and cash flow betas, along with noise betas. The results show that the residual, non-modeled news appears to be important in explaining the cross section of returns. Reassuringly, the results show that the cash flow betas, which command a price of risk of 29% per annum, matter in terms of statistical significance, a result that is perhaps not that surprising given the findings earlier in the paper showing that, using our model, dividend growth is more predictable than returns. Both the cash flow and noise betas contribute equally to the cross sectional explanatory power of the model.

The final set of cross sectional results we report in Panel C examines whether the use of different predictor variables in the return VAR makes a difference to the cross sectional analysis above. The results suggest that the cash flow beta and the noise beta are important in explaining the cross section of returns. Indeed, with the exception of the VARs containing *eqis* and *DP*, the estimate of λ_{CF} does not change by a great amount. Unfortunately, some of the return VAR specifications deliver a negative discount rate price of risk, a finding which presents problems when estimating the coefficient of risk aversion. This provides some support to the results in Chen and Zhao (2009) and shows that even if we are able to predict dividend growth and

estimate cash flow news directly, the results relating to the discount rate component, and their interpretation, are sensitive to the specification of the VAR predicting returns that is used to estimate discount rate news.¹⁷

V. Recent Stock Market Movements

In the previous sections, we have shown that the predictability of dividend growth has implications for both the time series and cross section of returns. An interesting recent use of discount rate and cash flow news is that of Campbell, Giglio and Polk (2010). They use discount rate and cash flow news estimated from both unrestricted VARs and a model that imposes ICAPM restrictions to examine the role of discount rate news and cash flow news in the boom-bust cycles of the late 1990s and early 2000s in particular. Campbell, Giglio and Polk (2010) follow Campbell and Vuolteenaho (2004) by estimating discount rate news and backing out cash flow news

¹⁷Campbell, Giglio and Polk (2010) estimate both the time series (the parameters in the return VAR) and the cross section (the coefficient of risk aversion) jointly by imposing restrictions derived from Campbell's (1993) discrete-time version of Merton's (1973) Intertemporal CAPM and estimating the resulting model by continuously updated GMM. Using quarterly data Campbell, Giglio and Polk (2010) have some success, the model delivering an estimated coefficient of risk aversion, γ , of 4.98, which seems reasonable. However, estimating this model proves very challenging with annual data, as we need for forecasting dividend growth. For a k -variable VAR and i test assets, Campbell, Giglio and Polk (2010) show that there are $k(k+1) + i + 1$ orthogonality conditions. Even with quarterly data, giving 319 observations, and only six test assets, for their 5-variable return VAR Campbell, Giglio and Polk (2010) are forced to impose several restrictions on the continuously updated GMM procedure to estimate the model. We attempted to estimate the model in Campbell, Giglio and Polk (2010) with our annual data but could not achieve convergence in the estimator. This is perhaps not surprising given that we only have 82 observations in total, have a similar number of predictor variables as Campbell, Giglio and Polk (2010), and we have VARs predicting both dividend growth and returns. Even using the same test assets as Campbell, Giglio and Polk (2010), we have in the region of 37 orthogonality conditions imposed on a highly nonlinear model with only 81 observations to estimate the model. Further, in their Monte Carlo experiments Hansen, Heaton and Yaron (1996) find that with a sample size of 100, despite the fact that the continuously updated GMM performs better than iterative and two-step methods, the large sample approximations are not very reliable and in the case where there are many moment conditions relative to the sample size, as is the case here, asymptotic theory gives poor guidance in terms of statistical inference.

as a residual from the return decomposition.¹⁸ They find that the technology boom and bust in the late 1990s/early 2000s was driven primarily by discount rate news while the downturn in the late 2000s was driven by cash flow news.

The results from section III of our paper, show that when we estimate cash flow news directly from a VAR that exploits the predictability of dividend growth that we identify, cash flow news becomes more important in explaining the variance of unexpected returns. The question we ask in this section is whether the increased importance of cash flow news affects any conclusions drawn about the proximate causes of booms and busts, especially more recent ones. From the return decomposition, an increase in either cash flow news and/or negative discount rate news implies an increase in stock prices.

Of particular interest is the behavior of cash flow news. Campbell, Giglio and Polk (2010) find that irrespective of the VAR they use to predict returns, cash flow news is negative during the early to mid 1990s before becoming positive towards the end of that decade, while discount rate news is positive.¹⁹ This leads Campbell, Giglio and Polk (2010) to conclude that discount rate news was the primary driver of the boom in returns in the 1990s and subsequent bust in the early 2000s. Campbell, Giglio and Polk (2010) also show that the more recent 2007–2009 downturn was a result of negative cash flow news.

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To examine whether estimating cash flow news directly has a bearing on this interpretation of recent events, Figure 1 plots smoothed versions of cash flow news estimated from the dividend growth VAR (top panel), negative discount rate news estimated from the return VAR (middle panel) and noise news (bottom panel), for the period 1990–2009.²⁰ The first panel of Figure 1

Figure 1 about here

¹⁸Campbell, Giglio and Polk (2010) add the default spread to the set of variables used in Campbell and Vuolteenaho (2004) to predict returns.

¹⁹This is particularly evident in the unrestricted VARs that Campbell, Giglio and Polk (2010) estimate. For the restricted model, the picture is slightly less clear in that cash flow news becomes slightly positive between approximately 1993 and 1995 before becoming negative again. It then remains negative until the turn of the century. The opposite pattern occurs in discount rate news.

²⁰Campbell, Giglio and Polk (2010) estimate the smoothed series as $MA_t(N) = 0.08N_t + (1 - 0.08)MA_{t-1}(N)$ where 0.08 is the smoothing parameter, N is the respective news term and $MA_t(N)$ is the smoothed news series. We calculate our smoothed series in the same way with the exception that as we use annual rather than quarterly

suggests that cash flow news has a more important role to play than that suggested by Campbell, Giglio and Polk (2010). In particular, when we estimate cash flow news directly by exploiting the predictability we identify earlier in the paper, the large run-up in returns experienced in the 1990s was driven by both cash flow and discount rate news while the downturn at the beginning of the 2000s appears to have been driven by negative cash flow news, something which is in contrast to the findings in Campbell, Giglio and Polk (2010) who find that discount rate news was responsible for this upturn and subsequent downturn.

Turning to the more recent 2007–2009 period, it would seem that negative cash flow news was largely responsible for this downturn. The negative of discount rate news exhibits a corresponding fall over this period but there was a corresponding increase in noise news which, to the extent that noise news could measure the error in calculating discount rate news, offsets the discount rate effect.

In summary, Campbell, Giglio and Polk (2010) argue that the 1990s boom and subsequent bust in 2002 was driven by discount rate news. Generally, when estimating cash flow news from a directly estimated predictive regression, we find the opposite in the sense that cash flow news also drove up prices throughout the 1990s and drove prices down between 2000–2002. We also find that cash flow news had a role to play in the subsequent upturn in stock markets through to 2007 and the fall in prices in the 2007–2009 period. Throughout this period, directly-estimated cash flow news has a greater impact on stock price movements than that using a measure of cash flow news backed out from the return decomposition.

VI. Conclusion

The literature on dividend growth and return predictability has emphasized two major findings. First dividend growth is unpredictable and, because returns are predictable, almost all variation in asset prices is driven by discount rate as opposed to cash flow news. Second, cash flow betas can explain the value premium puzzle. This raises an intriguing question: Why is news about

data, we annualize the smoothing parameter.

cash flow so important in the cross section of returns, but not in the time series?

Using a new variable based on a model of dividend smoothing, we find that dividend growth is strongly predictable and that this predictability has implications for both the time series of stock price movements and the cross section of stock returns. Using our new variable we are able to predict dividend growth from one to five year horizons, over the entire sample and in the post-war sample. Using the metric of \overline{R}^2 , the predictability of dividend growth that we identify is stronger than that of the stock return predictability that has been documented in the literature.

We assess the implications of predicting dividend growth using our model for the role of cash flow news in the time series and cross section of stock returns. We find that cash flow news does affect asset price variations when it is measured from a model that can predict dividend growth: discount rate news does not appear to be the only driver of stock prices.

In the cross section, in contrast to the cash flow betas estimated from backed-out cash flow news, as in Campbell and Vuolteenaho (2004), cash flow betas estimated using directly-estimated cash flow news from our model predicting dividend growth do not appear to be consistent with the value premium puzzle. Rather, they appear to be consistent with the size puzzle since small stock portfolios have higher cash flow betas than large stock portfolios. The pattern in noise betas, which arise due to any unmodeled residual after calculating cash flow and discount rate betas, appears consistent with the value premium puzzle.

Finally, we find that when we use cash flow news that is directly estimated from a VAR predicting dividend growth, cash flow news appears to have had a more important role in the recent stock market boom and busts of the 1990s and 2000s. The finding that the 1990s boom and subsequent bust of 2000–2002 is to some extent driven by cash flow news is in contrast to the results in Campbell, Giglio and Polk (2010) who show that it is driven by discount rate news. This finding highlights the potential importance of both cash flow news in stock prices and the necessity of directly estimating cash flow news.

Overall, in contrast to the extant literature, our new findings suggest: 1) dividend growth is strongly predictable; 2) exploiting this predictability to estimate cash flow news directly delivers

results suggesting that cash flow news is relatively more important in terms of understanding asset price variation through time; 3) cash flow betas appear consistent with the size and not the value premium puzzle if cash flow news is estimated directly from our model predicting dividend growth; and 4) the relative importance of cash flow news in explaining recent stock price run-ups and subsequent falls increases when cash flow news is estimated directly. However, we also sound a note of caution. While there is evidence that, at least with our model, cash flow news has a more important role than previously thought in explaining time series variation in stock returns, and cash flow betas calculated from directly-estimated cash flow news have an important role to play in explaining the cross section of returns, albeit with a different interpretation to that offered by Campbell and Vuolteenaho (2004), some of the return VAR specifications deliver a negative discount rate price of risk, a finding which presents some problems interpreting the asset pricing implications of the results. This latter finding provides some support to the results in Chen and Zhao (2009) and shows that even if we are able to predict dividend growth and estimate cash flow news directly, the results relating to the discount rate component, and their interpretation, are sensitive to the specification of the VAR predicting returns that is used to estimate discount rate news.

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Table 1
Predicting Dividend Growth With dpe

The table reports estimates of the parameters from the regression

$$\Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + \epsilon_{t+k}$$

where dpe_t is the cointegrating vector estimated from the Engle-Granger cointegrating regression $d_t = \beta_0 + \beta_1 p_t + \beta_2 e_t + dpe_t$. For the “Full Sample” panel, the estimated cointegrating vector using data from 1927–2009 is $dpe_t = d_t + 2.3322 - 0.2600p_t - 0.2563e_t$. For the “Post-War Sample” panel, the cointegrating vector is re-estimated using data from 1945–2009; the estimated cointegrating vector for the post-war sample is $dpe_t = d_t + 2.4790 - 0.2865p_t - 0.1874e_t$. Figures in parentheses beneath the parameter estimates are Newey-West t statistics correcting for heteroscedasticity and $k - 1$ th order autocorrelation. ***, ** and * denote significance at the 1, 5 and 10% levels respectively. \bar{R}^2 is the adjusted R^2 .

Full Sample				Post-War Sample			
k	δ_0	dpe_t	\bar{R}^2	k	δ_0	dpe_t	\bar{R}^2
1	0.0103 (1.0809)	-0.4889*** (-4.8373)	37%	1	0.0164** (2.2387)	-0.2656** (-2.4770)	23%
2	0.0162 (0.9393)	-0.8380*** (-4.1329)	37%	2	0.0352*** (2.6346)	-0.4284** (-2.0879)	17%
3	0.0259 (1.0812)	-0.8438*** (-3.4920)	28%	3	0.0543*** (2.9698)	-0.5791** (-2.1890)	20%
4	0.0357 (1.2055)	-0.8217*** (-3.6513)	23%	4	0.0721*** (3.1520)	-0.7706*** (-2.6350)	29%
5	0.0463 (1.3336)	-0.7595*** (-3.7690)	18%	5	0.0868*** (3.2325)	-0.8775*** (-3.1513)	34%

Table 2

**VAR Models for Estimating Discount Rate and Cash Flow News, Annual Data,
1928–2001**

The table reports estimates of the parameters from two VAR models that are used to estimate discount rate and cash flow news. The general form of the VAR model estimated is

$$\mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{u}_t$$

Panel A reports results for the VAR predicting returns, where \mathbf{z}'_t comprises real returns on the S&P 500 and the predictor variables used in Campbell and Vuolteenaho (2004). These are the term yield spread, TY , the price-earnings ratio, $PE10$, and the small-stock value spread, VS . TY is measured as the yield difference between 10-year constant-maturity taxable bonds and short-term taxable notes, $PE10$ is the log of the ratio of the S&P 500 price to a 10-year moving average of S&P 500 earnings and VS is the difference in the log book-to-market ratios of small value and small growth stocks. Panel B reports results for the VAR predicting dividend growth ($\mathbf{z}'_t = [\Delta d_t \ r_t \ dpe_t]$), where Δd_t is real dividend growth, r_t are real returns on the S&P 500 and dpe_t is the estimated cointegrating vector between log real dividends, log real prices and log real earnings for the S&P 500. Discount rate news is directly estimated using the VAR in Panel A while cash flow news is estimated directly using the VAR in Panel B. All variables are mean-adjusted. Figures in parentheses are t statistics. ***, ** and * denote significance at the 1, 5 and 10% levels respectively. \bar{R}^2 is the adjusted R^2 for the relevant equation. Panel C reports the variance of the return shock and the covariances of discount rate news and cash flow news with the return shock. For the row entitled ‘VAR from Panel A’, discount rate news, N_{DR} , is estimated from the Campbell-Vuolteenaho VAR predicting returns and cash flow news, N_{CF} , is calculated as a plug such that $u_{r,t} = N_{CF,t} - N_{DR,t}$ where $u_{r,t}$ is the return shock from the Campbell-Vuolteenaho VAR. For the row entitled ‘VAR from Panel B’, cash flow news is estimated and discount rate news is calculated as a plug such that $u_{r,t} = N_{CF,t} - N_{DR,t}$, where $u_{r,t}$ is the return shock from the VAR where \mathbf{z}_t contains $\Delta d_t, r_t$ and dpe_t . R^2_{DR} and R^2_{CF} are the R^2 s from regressions of the return shock on discount rate news and cash flow news respectively.

Panel A: Parameter Estimates, Campbell-Vuolteenaho VAR Predicting Returns

	Dependent Variable			
	r_t	TY_t	$PE10_t$	VS_t
r_{t-1}	0.0694 (0.5901)	-0.0028 (-0.0089)	0.1634 (1.3989)	-0.1155 (-1.2876)
TY_{t-1}	0.0298 (0.8254)	0.4946*** (5.1771)	0.0501 (1.4011)	-0.0557** (-2.0279)
$PE10_{t-1}$	-0.1655** (-2.5639)	-0.0065 (-0.0381)	0.8482*** (13.2347)	-0.0058 (-0.1175)
VS_{t-1}	-0.1206* (-1.9074)	0.4925*** (2.9398)	-0.0886 (-1.4117)	0.9601*** (19.9320)
\bar{R}^2	7%	44%	77%	87%

Panel B: Parameter Estimates, VAR Predicting Dividend Growth

	Dependent Variable		
	Δd_t	r_t	dpe_t
Δd_{t-1}	0.1140 (1.3144)	-0.4196** (-2.0970)	0.2690*** (2.8953)
r_{t-1}	0.2208*** (4.1233)	0.0024 (0.0192)	0.0441 (0.7685)
dpe_{t-1}	-0.3956*** (-4.5905)	-0.0372 (-0.1870)	0.6651*** (7.2068)
\bar{R}^2	46%	3%	46%

Panel C: Variance Decompositions

	$\sigma^2(u_r)$	$\sigma(u_r, -N_{DR})$	$\sigma(u_r, N_{CF})$	$R^2_{DR}(\%)$	$R^2_{CF}(\%)$
VAR from Panel A	0.0316	0.0246	0.0071	82.0	27.6
VAR from Panel B	0.0334	0.0225	0.0110	84.9	57.4

Table 3
Sensitivity of Discount Rate, Cash Flow and Noise News Variances and
Covariances To Different Return Predictor Variables, VARs Estimated Using
Annual Data, 1928–2001

The table reports the variance of unexpected returns ($\sigma(u_r^2)$) and covariances ($\sigma(i, j)$) of unexpected returns with discount rate news, cash flow news and noise news estimated from different VAR models. The general form of the VAR model is

$$\mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{u}_t$$

Discount rate news, N_{DR} , is estimated from VAR models that predict returns and cash flow news, N_{CF} , is estimated from the VAR model predicting dividend growth in Panel B of Table 2. For the various VAR models predicting returns, r_t are real returns on the S&P 500, $PE10$ is the PE ratio, measured as the log of the ratio of the S&P 500 price to a 10-year moving average of S&P 500 earnings, VS is the value spread, measured as the difference in the log book-to-market ratios of small value and small growth stocks, bm is the log of the book-to-market ratio used in Goyal and Welch (2008), measured as the log of the ratio of book value to market value for the Dow Jones Industrial Average, $eqis_t$ is the percent equity issuing used in Goyal and Welch (2008), measured as the ratio of equity issuing activity to total issuing activity, $PE1$ is the log one-year PE ratio and DP_t is the log dividend-price ratio. As both N_{DR} and N_{CF} are estimated from separate models, $N_{CF} - N_{DR}$ need not equal $u_{r,t}$. The difference is the residual that is not modeled. We label this as noise news, N_{NOISE} . R_{DR}^2 , R_{CF}^2 and R_N^2 are the R^2 s from regressions of the return shock on discount rate news, cash flow news and noise news respectively.

**Cash Flow News From Panel B of Table 2, Discount Rate News Estimated From The Return VAR Models
With Predictor Variables As Indicated Below, Noise News Estimated As The Return Shock
From The Return VAR Net Of Estimated Discount Rate and Cash Flow News**

Information Set, \mathbf{z}'_t	$\sigma(u_r^2)$	$\sigma(u_r, -N_{DR})$	$\sigma(u_r, N_{CF})$	$\sigma(u_r, N_{NOISE})$	$R^2_{DR}(\%)$	$R^2_{CF}(\%)$	$R^2_N(\%)$
$[r_t \quad TY_t \quad PE10_t \quad VS_t]$	0.0316	0.0246	0.0093	-0.0022	82.0	43.5	1.9
$[r_t \quad PE10_t \quad VS_t]$	0.0319	0.0251	0.0097	-0.0029	81.7	47.1	3.5
$[r_t \quad PE10_t \quad VS_t \quad bm_t]$	0.0287	0.0219	0.0092	-0.0024	69.3	47.4	1.8
$[r_t \quad PE10_t \quad VS_t \quad eqis_t]$	0.0272	0.0205	0.0077	-0.0009	77.5	34.9	0.3
$[r_t \quad PE10_t \quad VS_t \quad bm_t \quad eqis_t]$	0.0242	0.0174	0.0073	-0.0005	46.0	35.1	0.4
$[r_t \quad TY_t \quad PE1_t \quad VS_t]$	0.0336	0.0207	0.0099	0.0030	84.7	46.4	4.7
$[r_t \quad TY_t \quad DP_t \quad VS_t]$	0.0337	0.0194	0.0099	0.0044	54.9	47.0	5.4

Table 4

**Cash Flow and Discount Rate Betas For The 25 Fama-French Portfolios Sorted on
Market Capitalization and the Book-to-market Ratio**

The table reports estimated cash flow betas ($\widehat{\beta}_{CF}$) and discount rate betas ($\widehat{\beta}_{DR}$) for the 25 Fama-French portfolios sorted by market capitalization and the book-to-market ratio. The betas are calculated using cash flow and discount rate news estimated from the VAR models in table 2. The VAR we use to predict returns and estimate the return shock is from Panel A of Table 2 while the VAR we use to predict dividend growth is from Panel B of Table 2. As a point of reference, Panel A below reports betas calculated when discount rate news is directly estimated using the parameters from the return VAR and cash flow news is calculated as a plug such that $u_{r,t} = N_{CF,t} - N_{DR,t}$, where $u_{r,t}$ is the return shock from the return VAR. Panel B reports discount rate betas and cash flow betas when discount rate and cash flow news are estimated from separate VAR models. As both N_{DR} and N_{CF} are estimated from separate models, $N_{CF} - N_{DR}$ need not equal $u_{r,t}$. The difference is the residual that is not modeled. We label this as noise news (N_{NOISE}) and, following Chen and Zhao (2009) we calculate a beta for this news term as well. All of the variables used in the VARs are demeaned. *Growth* denotes lowest book-to-market ratio, *Value* denotes the highest book-to-market ratio, *Small* denotes smallest stocks by market capitalization and *Large* denotes the largest stock by market capitalization. ‘Difference’ is the difference between the *Value* and *Growth* betas and the *Large* and *Small* betas. ***, ** and * denote that, based on t statistics constructed from bootstrapped standard errors from 10,000 simulated realizations of the relevant VARs, the difference is significantly different from zero at the 1, 5 and 10% levels respectively.

Panel A: Cash Flow and Discount Rate Betas, VAR Predicting Returns, Discount Rate News Estimated, Cash Flow News Calculated As A Plug

β_{CF}	<i>Small</i>	2	3	4	<i>Large</i>	Difference
<i>Growth</i>	0.132	0.117	0.105	0.093	0.161	0.029
2	0.202	0.157	0.181	0.162	0.164	-0.038
3	0.282	0.266	0.239	0.255	0.187	-0.095***
4	0.268	0.292	0.276	0.307	0.292	0.024
<i>Value</i>	0.344	0.341	0.360	0.330	0.368	0.024
Difference	0.212***	0.224***	0.255***	0.237***	0.207***	

β_{DR}	<i>Small</i>	2	3	4	<i>Large</i>	Difference
<i>Growth</i>	1.209	1.078	1.096	0.908	0.835	-0.374***
2	1.194	1.036	0.947	0.868	0.732	-0.462***
3	1.127	0.976	0.875	0.853	0.747	-0.380***
4	1.271	0.982	0.852	0.855	0.791	-0.480***
<i>Value</i>	1.008	0.912	0.899	0.987	0.642	-0.366***
Difference	-0.201***	-0.166***	-0.197***	0.079**	-0.193***	

Panel B: Cash Flow, Discount Rate and Noise Betas, VAR Predicting Returns and Dividend Growth, Discount Rate News and Cash Flow News Estimated, Noise News Included

β_{CF}	<i>Small</i>	2	3	4	<i>Large</i>	Difference
<i>Growth</i>	0.463	0.392	0.398	0.330	0.340	-0.123***
2	0.419	0.399	0.374	0.317	0.320	-0.099***
3	0.449	0.414	0.389	0.384	0.343	-0.106***
4	0.463	0.412	0.373	0.390	0.391	-0.071**
<i>Value</i>	0.462	0.424	0.446	0.455	0.387	-0.075**
Difference	-0.001	0.032	0.048	0.125***	0.047	

β_{DR}	<i>Small</i>	2	3	4	<i>Large</i>	Difference
<i>Growth</i>	1.209	1.078	1.096	0.908	0.835	-0.374***
2	1.194	1.036	0.947	0.868	0.732	-0.462***
3	1.127	0.976	0.875	0.853	0.747	-0.380***
4	1.271	0.982	0.852	0.855	0.791	-0.480***
<i>Value</i>	1.008	0.912	0.899	0.987	0.642	-0.366***
Difference	-0.201***	-0.166***	-0.048	0.079**	-0.193***	

β_{NOISE}	<i>Small</i>	2	3	4	<i>Large</i>	Difference
<i>Growth</i>	-0.331	-0.275	-0.293	-0.237	-0.179	0.152***
2	-0.218	-0.242	-0.193	-0.155	-0.156	0.062
3	-0.168	-0.148	-0.150	-0.129	-0.156	0.012
4	-0.195	-0.119	-0.097	-0.083	-0.099	0.096***
<i>Value</i>	-0.118	-0.083	-0.085	-0.124	-0.019	0.099***
Difference	0.213***	0.192***	0.208***	0.113***	0.160***	

Table 5

**Cross-sectional Prices Of Risk and Pricing Errors, Different VAR Models
Predicting Returns**

The table reports estimates of the prices of risk from the cross-sectional regressions

$$R_i - R_f = \lambda_0 + \lambda_{DR}\widehat{\beta}_{DR} + \lambda_{CF}\widehat{\beta}_{CF} + \epsilon_i$$

and

$$R_i - R_f = \lambda_0 + \lambda_{DR}\widehat{\beta}_{DR} + \lambda_{CF}\widehat{\beta}_{CF} + \lambda_{NOISE}\widehat{\beta}_{NOISE} + \epsilon_i$$

where $R_i - R_f$ is the average excess return on test asset i , DR and CF denote discount rate and cash flow respectively, λ_{DR} , λ_{CF} and λ_{NOISE} denote the respective prices of risk and ϵ_i and ε_i denote the respective residuals. Discount rate, cash flow and noise news are estimated from VAR models. \overline{R}^2 is the adjusted R^2 from the relevant cross-sectional regression and Pricing Error is the weighted squared pricing error, calculated as either $\epsilon'\Sigma^{-1}\epsilon$ or $\varepsilon'\Sigma^{-1}\varepsilon$, where ϵ (ε) is the vector of residuals from the relevant cross-sectional regression and, following Campbell and Vuolteenaho (2004), Σ is a diagonal matrix where the i th diagonal element is the estimated return volatility for asset i . Figures in round parentheses are heteroscedasticity-consistent t statistics while figures in square parentheses are partial R^2 coefficients. The partial R^2 is the squared partial correlation coefficient, where the partial correlation coefficient measures the correlation between an explanatory variable and the dependent variable given the other explanatory variables. ***, **, and * denote significance at the 1, 5 and 10% levels respectively.

Panel A: Cash Flow and Discount Rate Betas both from the VAR Predicting Returns					
	λ_{DR}	λ_{CF}	λ_{NOISE}	\bar{R}^2	Pricing Error
	0.0567*** (3.2774) [17.7%]	0.3069*** (6.9569) [46.3%]		65%	0.0425
Panel B: Cash Flow Betas from the VAR Predicting Dividend Growth, Discount Rate Betas from the VAR Predicting Returns and Noise Beta from the residual news that is not modeled					
	λ_{DR}	λ_{CF}	λ_{NOISE}	\bar{R}^2	Pricing Error
	0.0636 (1.1461) [4.91%]	0.2928*** (2.8184) [24.9%]	0.3157*** (3.4974) [26.2%]	65%	0.0425
Panel C: VARs Predicting Returns and VAR Predicting Dividend Growth ($\mathbf{z}'_t = [\Delta d_t \ r_t \ dpe_t]$) Discount Rate News Estimated, Cash Flow News Estimated, Noise News As The Residual					
Information Set (Return VAR), \mathbf{z}'_t	λ_{DR}	λ_{CF}	λ_{NOISE}	\bar{R}^2	Pricing Error
$[r_t \ PE10_t \ VS_t \ bm_t]$	-0.0270 (-0.7051) [0.88%]	0.3417*** (4.7596) [30.4%]	0.1239*** (3.5204) [19.2%]	66%	0.0417
$[r_t \ PE10_t \ VS_t \ eqis_t]$	0.1526* (1.8772) [18.7%]	0.1699* (1.7552) [15.5%]	0.3529*** (3.2899) [33.4%]	65%	0.0419
$[r_t \ PE10_t \ VS_t \ bm_t \ eqis_t]$	-0.0709 (-1.2438) [2.29%]	0.3186*** (4.8650) [30.7%]	0.0241 (0.3642) [0.48%]	62%	0.0458
$[r_t \ TY_t \ PE1_t \ VS_t]$	-0.0182 (-0.3541) [0.70%]	0.2894** (2.3452) [26.8%]	0.2705*** (3.7299) [30.0%]	53%	0.0529
$[r_t \ TY_t \ DP_t \ VS_t]$	0.0372 (0.6543) [2.49%]	0.1878 (1.3406) [9.48%]	0.1239** (2.2067) [15.3%]	42%	0.0656

Figure 1

Smoothed Cash Flow, Discount Rate and Noise News, 1990–2009

The figure plots news terms estimated from VARs predicting dividend growth and returns. All of the news terms are smoothed, the smoothed series being estimated as $MA_t(N) = 0.32N_t + (1 - 0.32)MA_{t-1}(N)$ where N is the respective news term and $MA_t(N)$ is the smoothed news series. The first panel is cash flow news estimated directly from the VAR predicting dividend growth; the second panel is the negative of discount rate news estimated from the VAR predicting returns; the third panel is noise news, calculated as the return shock from the VAR predicting returns net of estimated cash flow and discount rate news.

