Time Variation in Cash Flows and Discount Rates*

Tolga Cenesizoglu[†]
Denada Ibrushi[‡]

Abstract

The relative contributions of cash flow and discount rate news to the conditional variance of market returns exhibit significant variation over time. We identify lagged changes in PPI inflation as the main macroeconomic determinant of this time variation. We analyze the economic importance of these results by allowing for time variation in cash flow and discount rate betas in Campbell and Vuolteenaho (2004) asset pricing framework. A conditional version of their two-beta framework not only provides reasonable estimates of risk prices and relative risk aversion coefficients but also outperforms other models in accounting for the cross-sectional variation in expected returns.

Key words: Multivariate Conditional Variance Models, Dynamic Conditional Correlation, Return Decomposition, PPI Inflation, Two-Beta Model

*We would like to thank Laurent Barras, Francesco Bianchi, Christian Dorion, Jefferson Duarte, Javier Gil-Bazo, Gunnar Grass, Alexandre Jeanneret, Feng Jiao, Simon van Norden, Amir Yaron, Anna Stepashova, Zhaneta Tancheva, and participants at McGill-HEC Doctoral Workshop and Doctoral Consortium at the Financial Management Association European Meeting.
[†]HEC Montréal and Alliance Manchester Business School, tolga.cenesizoglu@hec.ca, +1(514) 340-5668
[‡]HEC Montréal, denada.ibrushi@hec.ca, +1(438) 935-8111

1 Introduction

Stock prices vary over time due to either changes in investors' expectations about future cash flows, discount rates, or a combination of both. Which one of these two components is more important in determining stock price movements is a central question in finance. Hence, it is not surprising to find a large literature trying to answer this question.[1]

One challenge in answering this question is the fact that investors' expectations about neither future cash flows nor future discount rates are directly observable. Thus, one needs to obtain empirical proxies for investors' expectations of these two components. One such approach to obtain these proxies is the return decomposition approach of Campbell and Shiller (1988). Although there are some other alternatives, the return decomposition approach of Campbell and Shiller (1988) is by far the most popular, mostly due to its ease of implementation. Specifically, they first derive an identity that expresses unexpected returns as the difference between unexpected changes in investors' expectations of future cash flows and future discount rates, which they refer to as cash flow and discount rate news, respectively. To obtain empirical proxies for these two components, they suggest using a vector autoregressive framework to model the short-term dynamics of excess returns to obtain proxies for unexpected returns and discount rate news directly, while backing out cash flow news indirectly from the return decomposition identity. In other words, one only needs to estimate a linear vector autoregressive system with excess returns and a set of predictive variables to obtain proxies for cash flow and discount rate news.

Campbell and Shiller (1988) suggest that one can then answer the question "What moves stock prices?" based on these empirical proxies for cash flow and discount rate news. Specif-

[1] The list of articles includes, but is not limited to, Campbell (1991), Campbell and Ammer (1993), Campbell and Mei (1993), Vuolteenaho (2002), Campbell and Vuolteenaho (2004), Hecht and Vuolteenaho (2006), Chen and Zhao (2009), Campbell, Polk, and Vuolteenaho (2010), Koubouros, Malliaropulos, and Panopoulou (2010), Lustig and Verdelhan (2012), Engsted, Pedersen, and Tanggaard (2012), Campbell, Giglio, and Polk (2013), Chen, Da and Zhao (2013), Cenesizoglu (2014), Bianchi (2015) and Campbell, Giglio, Polk, and Turley (2017).

ically, they show that the variance of stock returns can be expressed as the sum of the variances of these two components minus two times their covariance. They then argue that the relative importance of each component in determining stock price movements can be analyzed based on their relative contributions to the overall variance of stock returns. This simple intuition combined with the ease of implementation lead to a large literature using this approach to analyze not only the sources of stock price movements, but also other related questions in finance, macroeconomics and accounting.[2] However, most studies analyze the relative importance of cash flow and discount rate news in determining the overall unconditional variance of stocks returns and do not consider the conditional variance and its potential variation over time.

In this paper, we fill this gap by analyzing the time variation in the relative importances of cash flow and discount rate news in determining the conditional, instead of unconditional, variance of market returns, as well as the macroeconomic determinants of this time variation and its economic importance. Similar to the previous literature, we obtain cash flow and discount rate news based on the return decomposition by considering a vector autoregressive system (VAR) with excess returns, term spread, dividend yield and small value spread as predictor variables. However, differently from the previous literature, we consider the decomposition of the conditional, rather than unconditional, variance of unexpected market returns. We do this by estimating a multivariate conditional variance model with dynamic conditional correlations (Engle (2002)) for cash flow and discount rate news. Compared to the unconditional variance decomposition, this approach allows us to decompose the conditional variance of market returns and analyze the time variation in the relative importance of its components.

In line with the stylized facts about the conditional variance dynamics of market returns

[2] In addition to those listed above, there are a few articles using the Campbell and Shiller (1988) approach in macrofinance, such as Bernanke and Kuttner (2005), and in accounting such as Callen and Segal (2004), Callen, Hope, and Segal (2005), and Callen, Livnat, and Segal (2006).

documented in the literature, we find that the conditional variances of its components vary significantly over time and are highly persistent but stationary. As the market goes through volatile and tranquil periods, the conditional variances of its components, not surprisingly, follow these dynamics closely. For example, both cash flow and discount rate news become, on average, more volatile in recessions compared to expansions. Furthermore, the conditional covariance between the two components also exhibits significant variation over time and is also persistent.

More importantly, the relative contribution of these components to the conditional variance of unexpected market returns also varies significantly over time. The contribution of discount rate news varies between 24% and 65% with a standard deviation of 9%, while that of cash flow news is less volatile and varies between 15% and 61% with a standard deviation of 7%. The contribution of the covariance varies between 10% and 45% with a standard deviation of approximately 6%. The discount rate news is more important than cash flow news during the beginning of the Great Depression. This changes in the middle of the Great Depression and cash flow news becomes more important than discount rate news. The cash flow news stays, on average, more important than the discount rate news between the mid-1930s and the mid-1950s, although there are still periods during which the opposite holds. However, since the mid-1950s, the relative importance of cash flow news steadily declines and the discount rate is the main determinant of conditional aggregate market movements. This changes once again around 2008 but this time more dramatically and the cash flow news becomes the main determinant during the Global Financial Crisis.

We analyze whether this time variation in the determinants of stock price movements is related to macroeconomic conditions. We consider four variables to capture macroeconomic conditions which have been shown to be important determinants of stock market volatility: industrial production index, producer price index, unemployment rate, and total nonfarm payroll. We first analyze whether these variables are related to the conditional variances of cash flow and discount rate news. We find that an increase in the industrial production index and nonfarm employment significantly decreases the conditional variance of cash flow news while an increase in the producer price index and unemployment significantly increases it. On the other hand, an increase in the producer price index significantly increases the conditional variance of discount rate news while all other variables have statistically insignificant effects. We then turn our attention to the effect of these variables on the relative importances of cash flow and discount rate news; we find the producer price index to be the only variable with a statistically significant effect. Specifically, an increase in the PPI inflation (inflation) rate makes the cash flow news more, and discount rate news less, important in determining the conditional variance of market returns. Furthermore, the effects of inflation on the relative importances of cash flow and discount rate news are significantly different from each other.

Having identified inflation as the main determinant, we take a closer look at its effect on the time variation in the conditional variance decomposition of market returns. We first distinguish between positive and negative changes in the producer price index to analyze any asymmetries between the effects of an increase and a decrease in inflation. We find that an increase in inflation significantly increases the relative importance of cash flow news while it decreases the relative importances of both discount rate news and the conditional covariance components, although insignificantly. The opposite holds for a decrease in inflation. We then distinguish between expected and unexpected inflation. We find that it is the unexpected, and not the expected, inflation that drives the relative importance of both components. An increase in the unexpected inflation significantly increases the relative importance of cash flow news and significantly decreases that of discount rate news. We also distinguish between expansion and recession periods as defined by the National Bureau of Economic Research (NBER) and analyze any asymmetries over the business cycles. An increase in inflation significantly increases the relative importance of cash flow news in both expansions and recessions, with a slightly bigger effect in recessions. Inflation does not have a significant effect on the relative importance of discount rate news when we distinguish between expansions and recessions. We also analyze its long-term effect based on impulse response functions obtained from a VAR that includes the relative importance of cash flow and discount rate news and changes in inflation. A positive shock to inflation increases the relative importance of both components in the long run.

Finally, we turn our attention to the economic importance of our results by estimating a conditional version of the Campbell and Vuolteenaho's (2004) (CV) framework. We argue that it is economically important to account for time variation in decomposing the portfolio's overall beta with the market if a model which captures this time variation performs better than models ignoring it. To this end, we consider a conditional version of the two-beta framework with time-varying betas obtained by estimating multivariate conditional variance models for cash flow news, discount rate news and demeaned returns on the 25 size and book-to-market portfolios one at a time. We show that this conditional asset pricing model provides reasonable estimates of risk prices and relative risk aversion coefficients, and performs much better than several alternative models, such as the unconditional CV two-beta model, CAPM and the three-factor model of Fama and French (1996), in several dimensions. First, the constant is not significantly different from zero in both the constrained and unconstrained estimation of this model, while the same cannot be said for most competitor models considered. Second, the cash flow news has a significantly positive risk price of approximately 1.6% per month (19% per annum), which is quite reasonable, while other models produce either too high or insignificant risk prices. Third, this conditional framework implies very reasonable values for the relative risk aversion coefficient of between 3 and 11, while other models sometimes imply negative coefficients. Finally, this model accounts for slightly more than 60% of the variation in the cross-section of expected returns, which is on par with the Fama–French three-factor model and better than other conditional and unconditional models.

The paper proceeds as follows: Section 2 describes the approach to obtain proxies for cash flow and discount rate news. Section 3 presents the model for estimating conditional variances and covariance, and reports the empirical results for time variation in the conditional variance decomposition of returns. Section 4 studies the relation between decomposition of conditional variance of the market and main macroeconomic indicators. Section 5 presents the pricing implications of our time-varying approach, and Section 6 concludes.

2 Cash Flow and Discount Rate Proxies

In this section, we first briefly discuss the Campbell and Shiller (1988) return decomposition approach before discussing our empirical choices for its implementation. Based on the log-linear approximation of returns in Campbell and Shiller (1988), Campbell (1991) shows that unexpected returns can be decomposed into changes in investors' expectations about discounted sum of future cash flows and discount rates, which are generally referred to as cash flow (CF) and discount rate (DR) news, respectively. Specifically, Campbell (1991) derives the following relation:

$$\begin{aligned} r_{m,t+1} - E_t r_{m,t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \triangle d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j} \\ &= CF_{t+1} - DR_{t+1} \end{aligned} \tag{1}$$

where E_t represents expectation at time t. $r_{m,t}$ and d_t denote log returns and dividends at time t, respectively, and ρ is a parameter of linearization that depends on the long-term mean of the log dividend–price ratio. Equation (1) suggests that unexpected returns are higher if future cash flows are higher than expected or future discount rates are lower than expected or a combination of the two. One can then analyze the overall contribution of each component by decomposing the unconditional variance of unexpected return r as follows:

$$var\left(r_{t+1}\right) = var\left(CF_{t+1}\right) + var\left(DR_{t+1}\right) - 2cov\left(CF_{t+1}, DR_{t+1}\right) \tag{2}$$

The ratio of each component on the right-hand side of Equation (2) to unconditional variance of stock returns can then be interpreted as the relative contribution of that component in determining the overall movements in stock prices.

To implement this decomposition empirically, Campbell and Shiller (1988) propose modeling the short-run dynamics of expected returns to obtain forecasts of future expected returns and, thus, a proxy for discount rate news and back out cash flow news from Equation (1). They also suggest that this can be easily achieved in a VAR of order one which includes returns and its common predictors. Thus, the standard approach in the literature is to estimate the following VAR (1):

$$\mathrm{Z}_{t+1} {=} \alpha + \mathit{\Pi}\mathrm{Z}_t + u_{t+1} \tag{3}$$

where Z_t is a $(n \times 1)$ vector whose first element is the market return and other elements are variables that might have some power in predicting market returns. Proxies for cash flow and discount rate news can then be obtained based on estimated VAR parameters and a choice of ρ as follows:

$$\begin{aligned} \widehat{DR}_{t+1} &= e1'\hat{\lambda}\hat{u}_{t+1} \\ \widehat{CF}_{t+1} &= (e1' + e1'\hat{\lambda})\hat{u}_{t+1} \end{aligned} \tag{4}$$

where $e1$ is a $(n \times 1)$ vector whose first element is equal to one while others are equal to zero and $\hat{\lambda} {\equiv} \rho\hat{\mathit{\Pi}}(I - \rho\hat{\mathit{\Pi}})^{-1}$.

The final step in the empirical implementation of the standard approach is to choose a value for ρ and, more importantly, the variables to include in the VAR as predictors for the market return. As mentioned above, ρ is a function of the long-run mean of the log dividend–price ratio and, thus, can be easily estimated. We choose ρ to be equal to 0.996 for our set of monthly data. As discussed above, the first variable in the VAR system is the market return, which we proxy by the continuously compounded excess return on the Standard & Poor's (S&P) 500 index. The choice of predictor variables is much more difficult. This is mostly due to the fact that the empirical results tend to be quite sensitive to the choice of predictor variables, as shown in Chen and Zhao (2009). That said, Engsted, Pedersen and Tanggaard (2012) argue that this sensitivity is reduced when one includes a price-scaled variable as a predictor variable in the VAR system. More specifically, they show that one needs to include the dividend–price ratio for the VAR to be theoretically valid.

In this paper, we follow their suggestion and include dividend–price ratio as our price-scaled variable. In addition to dividend–price ratio (dp), we include term spread (tms) and small stock value spread (svs) in the VAR system for our main set of results. Term spread is the difference between long-term yield on government bonds and Treasury-bill yield, and dividend–price ratio is the logarithm of the ratio of 12-month moving sum of dividends to price. Both of these variables are from Amit Goyal's website. Small stock value spread is obtained by subtracting the log book-to-market ratio of small growth stocks from the log book-to-market ratio of small value stocks as in CV. We use the six size and book-to-market sorted portfolios from Ken French's website to compute small stock value spread. While term spread and dividend price ratio have been widely used as predictors in the literature, CV propose small stock value spread as a predictor of market returns. They argue that ICAPM rectifies the value anomaly once small value stock returns forecast higher market returns, and small growth stock returns lower market returns. In each section, we discuss the robustness of our results to using alternative sets of predictor variables.

We obtain monthly proxies for cash flow and discount rate news by estimating the VAR system using monthly data between 1929 and 2014. Table 1 presents some summary statistics for the variables in the VAR system.

[Insert Table 1 about here]

Table 2 presents the estimates of the parameters in the VAR system. The first row is the equation for returns and suggests that lagged returns, term spread and dividend yield have predictive information about returns but the associated adjusted R^2 is low, suggesting that the overall predictive power of these variables is low, as it is well known. The predictor variables are highly persistent with autoregressive coefficients varying between 0.96 and 0.99. The dividend yield is predicted also by lagged return and lagged term spread.

[Insert Table 2 about here]

Table 3 presents the decomposition of the unconditional variance in Equation (2) for S&P 500 returns in basis points, i.e. the variance estimates are multiplied by 10,000, as well as the relative contribution of each component. The unconditional variance of unexpected S&P 500 returns (in basis points) is about 30 during our sample period. Discount rate and cash flow news explain 36% and 30% of the unconditional variance of S&P 500 returns, respectively, while the remaining 33% is due to the covariance between the two components. These results are broadly consistent with those in literature. For example, Chen and Zhao (2009) also report approximately equal contributions of CF and DR news to the unconditional market variance when dividend yield is used instead of the price–earnings ratio in the VAR system.

[Insert Table 3 about here]

3 Time Variation in Cash Flows and Discount Rates

It is well known that the conditional variance of market returns exhibits significant variation over time. This in turn implies that the components of the market return, i.e. cash flow and discount rate news, might also have time varying conditional variances and covariances.

More importantly, the contributions of these components to the conditional variances of stock returns might also be changing over time and might be quite different from their contributions to the overall unconditional variance.

In this section, we analyze the time variation in the contribution of each component in determining the conditional variance of market returns. One can obtain the conditional variance decomposition of market returns by replacing the unconditional quantities in Equation (2) with their conditional counterparts. This, of course, requires proxies for the conditional variances of each component as well as for their conditional covariance. We do this by estimating multivariate conditional variance models for cash flow and discount rate news. Specifically, we consider the dynamic conditional correlation model (DCC) of Engle (2002) where the conditional variance of each component is modeled as a univariate symmetric GARCH(1,1) model and the correlations have their own autoregressive dynamics. Given that both cash flows and discount rates have zero mean by construction, we can directly model their conditional variances and correlations without having to estimate a specification for their mean. Let η_{t+1} denote the (2×1) vector of cash flow and discount rate news at time $t+1$, i.e. $\eta_{t+1} = [CF_{t+1}, DR_{t+1}]'$, and $\sum_t$ denote their (2×1) conditional variance matrix based on information at time t. We then model

$$\begin{aligned} \sum\nolimits_t &= \begin{bmatrix} var_t(CF_{t+1}) & cov_t(CF_{t+1}, DR_{t+1}) \\ cov_t(CF_{t+1}, DR_{t+1}) & var_t(DR_{t+1}) \end{bmatrix} \\ &= \begin{bmatrix} \sigma^2_{CF,t} & \sigma_{CF,DR,t} \\ \sigma_{CF,DR,t} & \sigma^2_{DR,t} \end{bmatrix} \qquad (5) \\ &= D_t R_t D_t \end{aligned}$$

where

$$R_t = Q_t \oslash Q_t^*,$$

$$Q_t = (1 - a - b)\, \bar{R} + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1}, \tag{6}$$

$$Q_t^* = \begin{bmatrix} q_{CF,t} & \sqrt{q_{CF,DR,t}} \\ \sqrt{q_{CF,DR,t}} & q_{DR,t} \end{bmatrix}$$

and ε_t is the (2×1) vector of standardized cash flow and discount rate news, i.e. $\varepsilon_t = [{}^{CF_t}/_{\sigma_{CF,t}}, {}^{DR_t}/_{\sigma_{DR,t}}]$, and $\oslash$ denotes element-by-element division. D_t is the diagonal matrix with conditional standard deviations of cash flow and discount rate news, i.e. $D_t = [\sigma_{CF,t}, \sigma_{DR,t}]$, which themselves are modeled as GARCH(1,1) processes. The DCC MVGARCH model is estimated via maximum likelihood based on a three-step approach. The first step fits univariate symmetric GARCH(1,1) models for cash flow and discount rate news. The second step estimates the constant conditional correlation based on the usual correlation estimator using the standardized residuals. The final step consists of plugging the correlation estimate into the equation for Q_t to obtain the estimates of a and b, which govern the dynamics of the conditional correlations. Table 4 presents the results from the estimation of this model.

[Insert Table 4 about here]

Given the stylized facts about the conditional variance dynamics of market returns, it is not surprising to find that the conditional variances of its components are time-varying and highly persistent, but stationary. Furthermore, their conditional correlation is also time-varying and highly persistent. Figure 1 presents this time variation in conditional variance of cash flow and discount rate news and their conditional covariance along with the conditional variance of market returns between 1929 and 2014.

[Insert Figure 1 about here]

As the market goes through volatile and tranquil periods, the conditional variances of its components, not surprisingly, follow these movements closely. For example, it is well known that market returns tend to be more volatile during recessions compared to expansions. It is then not surprising that both cash flow and discount rate news also become, on average, more volatile in recessions compared to expansions. However, several interesting, and not necessarily expected, facts emerge from Figure 1. First, there are some periods during which one of the components becomes more volatile while the other does not. For example, discount rate news becomes considerably more volatile than cash flow news during the recession caused by the 1973 oil crisis. Second, the conditional covariance between cash flow and discount rate news increases (in magnitude) in recessions, especially during the Great Depression, the oil crises and the Global Financial Crisis. Last but not least, discount rate news seems to be relatively more volatile, on average, than cash flow news. That said, this relation seems to change over time and cash flow news is more volatile during most of the Great Depression and for several months during the Global Financial Crisis. Overall, these results suggest that the conditional variance of cash flow and discount rate news, as well as their conditional covariance, vary significantly over time. More importantly, these time variations are not symmetric and exhibit significant differences during certain periods. This, in turn, implies that the relative contribution of each component to the conditional variance of market returns also varies over time.

To analyze more closely the time variation in the relative contribution of each component to the conditional variance of market returns, we compute the ratio of the conditional variance of each component as well as their conditional covariance to the conditional variance of unexpected market returns, i.e.$\sigma^2_{CF,t}/\sigma^2_{m,t}$, $\sigma^2_{DR,t}/\sigma^2_{m,t}$, $-2\sigma(CF,DR)_t/\sigma^2_{m,t}$. The sum of these ratios is equal to one.

Table 5 presents some basic summary statistics on these ratios. The cash flow and discount rate news contribute, on average, about 30% and 41% to the conditional variance of market returns, and their conditional covariance contributes, on average, about 29%. These results are very similar to the unconditional variance decomposition of market returns reported in Table 3. The contribution of discount rate news varies between 24% and 65% with a standard deviation of 9%, while that of cash flow news is less volatile and varies between 15% and 61% with a standard deviation of 7%. The contribution of the covariance varies between 10% and 45% with a standard deviation of approximately 6%.

[Insert Table 5 about here]

Figure 2 presents the variation of these ratios over time. The contribution of both components to the conditional variance of market returns varies significantly over time. The relative importance of discount rate news increases, on average, since the Great Depression and reaches its peak around the burst of the dotcom bubble and the 2001 recession. It then steadily declines up until the end of the Global Financial Crisis around 2011 and 2012. The relative importance of cash flow news is comparatively more stable in the earlier sample period up until the early 1960s. It then starts to decline and stays at a lower level up until the recession caused by the Global Financial Crisis when it jumps and reaches its highest level. Campbell et al. (2013) argue that the 2001 downturn is mainly related to positive revisions in return expectations, while the Global Financial Crisis is mainly related to negative revisions in cash flows. CV also analyze the relationship between the two types of news and NBER cycles. Similarly, they associate the 2001 crisis with rising discount rates, and the Great Depression with both CF and DR news. Different from our work, inferences in both of these papers are based on smoothed news levels rather than on conditional variances.

[Insert Figure 2 about here]

It is also easy to see from Figure 2 that the increase in the relative importance of discount rate news comes at the expense of the relative importance of the conditional covariance between cash flow and discount rate news. To be more precise, the relative importance of the conditional covariance decreases from about 45% in 1929 to about 15% around the early 1950s. Its contribution then stays around 25%, starts to decline in the early 1990s, and reaches its lowest values during the 2001 and 2008 recessions.

To understand the time variation in the contribution of cash flow relative to that of discount rate news, we also compute the ratio of the conditional variances of cash flow and discount rate news, i.e. $\sigma^2_{CF,t}/\sigma^2_{DR,t}$. Figure 3 presents the variation of this ratio over time, where a ratio greater than one implies that the conditional variance of cash flow news is relatively more important than that of discount rate news in determining the conditional variance of market returns.

[Insert Figure 3 about here]

The cash flow news is more important than discount rate news for about one third of our sample period. However, this changes significantly over time. For example, the cash flow news is, on average, the main determinant of the conditional market variance in the earlier part of the sample before the mid-1950s, although there are still periods, especially recessions, during which discount rate news becomes more important relative to the cash flow news. However, the discount rate is the main determinant of the conditional market variance between the mid-1950s and the Global Financial Crisis. This changes dramatically during the Global Financial Crisis and the cash flow news once again becomes the main determinant. These results about the Global Financial Crisis are consistent with those in Campbell et al. (2013).

3.1 Robustness Checks

In this section, we analyze the robustness of these results to making alternative empirical choices. We performed all the analysis discussed above under alternative empirical assumptions. For the sake of brevity, we summarize our findings without presenting any results.

We start with the robustness of our results to using alternative predictor variables in the original VAR system used to obtain cash flow and discount rate proxies. As discussed in Section 2, it is well known that the return decomposition approach of Campbell and Shiller (1988) tends to be sensitive to the choice of predictor variables in the VAR system. To analyze whether this sensitivity affects our findings, we consider several alternative sets of predictor variables in the VAR system. In all these different specifications, we always include a price-scaled variable, such as dividend yield or price–earnings ratio, since Engsted, Pedersen and Tanggaard (2012) argue that a price-scaled variable is required for the VAR system to be valid and stress the fact that dividend yield is indeed the theoretically correct one. Specifically, we perform the above analysis using cash flow and discount rate news proxies obtained based on the following sets of predictor variables: (1) excess returns, term spread, price–earnings ratio, small stock value spread; (2) excess returns, term spread, dividend yield, small stock value spread, default spread. Our findings suggest that cash flow and discount rate proxies based on different sets of predictor variables are highly correlated with each other. The conditional variances of CF and DR news based on the original set of predictor variables have 0.94 and 0.71 correlations with those based on the first set of alternative predictor variables. We find an approximate correlation of 0.93 between CF and DR variances obtained from our original set of state variables and their counterparts from the second set of alternative predictor variables. However, our results also confirm the findings of the previous literature on the sensitivity of the unconditional variance decomposition. That said, we find that conditional variance decomposition is much less sensitive to the choice of predictor variables than the unconditional variance decomposition. More importantly, as we will discuss below, our findings on the relation between relative importances and macroeconomic variables are robust to using alternative sets of predictor variables. Finally, we also consider different values for ρ, which do not yield qualitatively different conditional variances of cash flow and discount rate news or relative importance ratios.

Following CV, we also distinguish between the early sample (1929–1963) and the modern sample (1963–2014). There are two main reasons motivating this split. First, the results emerging from the earlier period are highly affected by the Great Depression. As CV remark, it is quite reasonable to believe that during these early years most of the unconditional variance is attributed to CF news due to the fact that the sample is dominated by highly leveraged firms. CV show that DR uncertainty is almost flat during this period, thus explaining why their two-beta model and CAPM perform equally well for these months. The second reason emanates from the adjustments in stock market listing prerequisites. While in the early period there existed strong profitability requirements for stocks to be listed, in the late 1970s NASDAQ stocks were added to the NYSE to benefit from equity financing. Hence, this scenario also supports the idea that CF was unsurprisingly more important than DR during the pre-1963 period, well before firms with high exposure to DR risk started co-existing in the index. In this paper, we mostly focus on the overall sample since we consider time variation and can analyze different periods individually. Furthermore, as in Bianchi (2015), we also believe that the extreme events in the early sample period affect investors' expectations and should therefore be included when obtaining empirical proxies. Nevertheless, we still obtain cash flow and discount rate news for the modern sample period by estimating the VAR system in the modern sample and thus completely ignoring the early sample period. We find that our original cash flow and discount rate news are highly correlated with these ones.

We also performed a further decomposition of the discount rate news into unexpected changes in investors' expectations about future risk premia and risk-free rate. Engsted, Pedersen and Tanggaard (2012) suggest that risk-free rate should be a right-hand variable based on the fact that we are predicting the excess returns on the left-hand side. To this end, we included the risk-free rate as an additional predictor variable in the VAR system in Equation (3). One can then decompose the unexpected returns into news about cash flows, risk premia and riskless rate following Campbell and Ammer (1993). This decomposition is very similar to the standard Campbell and Shiller (1988) decomposition and we, thus, refer the reader to the Campbell and Ammer (1993) for additional details. The obtained conditional variances show to be almost perfectly correlated with the conditional variances from our model where risk-free rate is not a predictor variable. The results remain robust when we estimate VAR under the modern sample instead of the whole sample.

4 What Explains the Time Variation in Cash Flows and Discount Rates?

So far, we have documented significant time variation in the relative importance of different components in determining the conditional variance of market returns. We have also alluded to the possibility that this time variation might be related to economic conditions. In this section, we analyze the relation between the conditional variance decomposition of market returns and macroeconomic conditions. To do this, we consider four variables to capture macroeconomic conditions: industrial production index (*ip*), producer price index (*ppi*), unemployment rate (*unemp*) and total nonfarm payroll (*emp*). We choose to focus on these four variables following the previous literature, such as Schwert (1989), Flannery and Protopapadakis (2002) and Engle et al. (2013), which show these four variables to be important determinants of stock market volatility. These variables are available from the Federal Reserve Bank of St. Louis and we consider their latest available vintage. We restrict the sample period to between 1948 and 2014 since the unemployment rate is only available starting 1948. We start by analyzing whether these variables have an effect on the conditional variance of unexpected market returns. To this end, we estimate the following GARCH(1,1) specification with lagged exogenous variables for the conditional variance of unexpected market returns:

$$\sigma_{m,t}^2 = exp\left(\gamma_m^{'} X_{t-1}\right) + \alpha_m \varepsilon_{m,t-1}^2 + \beta_m \sigma_{m,t-1}^2 \tag{7}$$

where X_{t-1} is a $(k \times 1)$ vector of lagged exogenous variables including a constant. We analyze the effect of exogenous variables in exponential form to guarantee that the estimated variance is positive without having to impose restrictions on their coefficients. We first consider the lagged (log) changes of these macroeconomic variables separately and then jointly as exogenous variables in the conditional variance specification.[3] When considered both separately and jointly, the change in the producer price index is the only variable that has a significant effect on the conditional variance of unexpected returns. An increase in the producer price index increases the conditional variance of unexpected returns on the aggregate index, in line with the findings in the previous literature.

A variable might still have a significant effect on the conditional variances of the components, even if it does not have a significant effect on the conditional variance of unexpected returns. To this end, we now analyze the effect of these variables on the conditional variances of cash flow and discount rate news. We estimate the GARCH(1,1) specification with exogenous variables in Equation (7), rather than a simple GARCH(1,1) specification, in the first step of a multivariate dynamic conditional correlation specification similar to that in Equation (5) and Equation (6). The columns titled CF and DR in Table 6 present the coefficient estimates of macroeconomic variables in the conditional variance specifications of cash flow and discount rate news, respectively. The column titled F-stat presents the F-statistic of the null hypothesis that the coefficient estimates of a given macroeconomic variable are equal in the conditional variance specifications of cash flow and discount rate news. We start with

[3] We also considered lagged (log) changes of these variables separately as well as jointly in the mean equation for unexpected returns. None of them has a statistically significant effect in the mean equation of unexpected returns in separate and joint regressions at the 5% level. To be consistent with our analysis in Section 3, we present the results based on the estimation without controlling for the effect of these variables in the mean equation of unexpected returns. Nevertheless, we analyzed the effect of these macroeconomic variables on the conditional variance of unexpected returns after having removed their effect on the mean of unexpected returns and our results are very similar to those presented.

the results in Panel (a) where we consider the effect of each macroeconomic variable separately. An increase in the industrial production index and nonfarm employment significantly decreases the conditional variance of cash flow news, while an increase in the producer price index and unemployment significantly increases it. On the other hand, an increase in the producer price index significantly increases the conditional variance of discount rate news while all other variables have statistically insignificant effects. When we consider the effect of these variables jointly, our results remain similar. The only exception is the effect of the industrial production index on the conditional variance of cash flow news which becomes statistically insignificant when we control for the effect of other variables. In both separate and joint specifications, none of the macroeconomic variables has statistically different effects on the conditional variances of cash flow and discount rate news.

[Insert Table 6 about here]

We now analyze whether macroeconomic conditions affect the relative importance of cash flow and discount rate news in determining the conditional variance of unexpected returns. We do this by regressing the relative importance of cash flow and discount rate news on the macroeconomic variables. We do not consider the relative importance of their conditional covariance since it is simply one minus the sum of the relative importances of cash flow and discount rate news. Given that we only consider linear effects in our regressions, one can simply compute the effect of a given macroeconomic variable on the relative importance of the conditional covariance as the negative of the sum of its effects on relative importances of cash flow and discount rate news. Given that the relative importances of both components are quite persistent, as discussed in Section 3, we control for their lagged values in these regressions. To be more precise, we estimate the following specification via seemingly unrelated regressions:[4]

[4]

$$
\begin{aligned}
\sigma^2_{CF,t}/\sigma^2_{m,t} &= \theta'_{CF} X_{t-1} + \phi_{11} \sigma^2_{CF,t-1}/\sigma^2_{m,t-1} + \phi_{12} \sigma^2_{DR,t-1}/\sigma^2_{m,t-1} + \epsilon_{CF,t} \\
\sigma^2_{DR,t}/\sigma^2_{m,t} &= \theta'_{DR} X_{t-1} + \phi_{21} \sigma^2_{CF,t-1}/\sigma^2_{m,t-1} + \phi_{22} \sigma^2_{DR,t-1}/\sigma^2_{m,t-1} + \epsilon_{DR,t}
\end{aligned} \tag{8}
$$

Table 7 presents the coefficient estimates on the macroeconomic variables from the estimation of the regression models in Equation (8) as well as their differences and the negative of their sum from the equations for cash flow and discount rate news.

[Insert Table 7 about here]

The producer price index is the only variable that has significant effects on the relative importances of CF and DR news. Specifically, an increase in the producer price index increases the relative importance of the cash flow conditional variance while it decreases the relative importances of discount rate conditional variance and their conditional covariance. In other words, an increase in inflation makes the cash flow news more important in determining the conditional variance of returns at the expense of discount rate news. Furthermore, the effects of inflation on the relative importances of cash flow and discount rate news are significantly different from each other.

Having identified inflation as the main determinant of the conditional variances of cash flow and discount rate news, as well as their relative contributions to the conditional variance of unexpected returns, we focus on the effect of inflation on the conditional variance decomposition. We first discuss the intuition behind why inflation affects the conditional variance decomposition. We then break down its total effect in several dimensions.[5]

We also estimated this specification via generalized method of moments where we use X_{t-1} , $\sigma^2_{CF,t-1}/\sigma^2_{m,t-1}$ and $\sigma^2_{DR,t-1}/\sigma^2_{m,t-1}$ as instruments. This allows us to obtain the same coefficient estimates as SUR estimation but correct the standard errors via heteroscedasticity and autocorrelation consistent standard errors à la Newey–West. Our conclusions based on HAC standard errors remain similar to those presented.

[5] We performed all the analysis below for the other variables but we did not find any significant results,

4.1 Discussion on the Effect of Inflation

Many studies as early as Officer (1973) have analyzed the relation between stock market volatility and macroeconomic variables. In a widely-cited paper, Schwert (1989) relates stock market volatility to the level and volatility of macroeconomic activity. Following the seminal paper of Schwert (1989), Engle et al. (2013) also analyze the effect of inflation and industrial production on stock market volatility. Specifically, they find that increases in industrial production decrease volatility and more inflation leads to high stock market volatility. Given these results, it is then not too surprising to find that industrial production and inflation have similar effects on the conditional variances of the cash flow and discount rate news. What is interesting in our results is the finding that an increase in the inflation rate makes cash flow news more important in determining the conditional variance of market returns. Before discussing potential explanations for why cash flow news might become relatively more important following an increase in inflation, we discuss some further results related to this finding. In our main set of results, we decompose the log returns in excess of the risk-free rate into cash flow and discount rate news. Although these returns are nominal, in the strict sense of the word, we believe that using log returns in excess of the risk-free rate removes the direct effect of inflation on our decomposition. In other words, we believe that our finding on the effect of inflation on the relative importance of cash flow news cannot be explained by our use of "nominal returns" in excess of the risk-free rate. We nevertheless consider decomposing the real returns, computed as the log returns in excess of the inflation rate. We first show that they are indeed highly correlated (98%) with log returns in excess of the risk-free rate. We then proceed to perform the same analysis above in Section 4, and find that an increase in the inflation rate makes cash flow news more important in determining the conditional variance of real market returns. As mentioned in Section 3.1, one can also consider a further decomposition of the nominal returns into news about cash

confirming that inflation is the main determinant of the conditional variance decomposition of unexpected returns.

flows, discount rates and real-rate of returns. When we consider this further decomposition, we find that the log change in the producer price index continues to increase significantly the relative importance of cash flow news in determining the conditional variance of nominal market returns, while it significantly (at 10% level) decreases that of discount rate news and increases, but insignificantly so, that of news about real-rate of returns. Overall, these two sets of additional results suggest that our main finding about the effect of inflation on the relative importance of cash flow news is not due to using "nominal" excess returns. We now turn our attention to other potential explanations. Although there are several theoretical models relating inflation to stock market volatility (see for example David and Veronesi (2013)), these studies do not provide much theoretical guidance on our finding since they treat inflation as a fundamental alongside cash flow and discount rate news. One such potential explanation might follow from the relation between inflation and uncertainty about economic activity and policy. It is well known, at least since Friedman (1977), that an increase in inflation creates higher economic uncertainty (see for example Holland (1995)). There is also a literature in corporate finance documenting that higher economic uncertainty results in higher uncertainty about firms' investment decisions and, thus, their cash flows. Although higher inflation might also increase uncertainty about future discount rates, one would expect this effect to be stronger for cash flows than discount rates. Based on these two channels, it is then not difficult to argue that cash flows become more volatile than discount rates following an increase in inflation. Another potential explanation might be tax-related. For example, Feldstein (1980) argues that higher inflation can reduce real profits through its effect on taxes paid by firms on their earnings. To be more precise, taxable profits in the US are computed by subtracting depreciation from net operating income. This depreciation amount depends on the book value of the asset rather than its market value. When inflation increases, this method of depreciation, called historic-cost depreciation, causes the real value of the tax shield provided by the depreciation and, thus, the real taxable profits, to decrease. He also argues that this effect of inflation might be smaller on the discount rates compared to earnings. However, he does not explicitly discuss the effect of inflation on the volatility of earnings and discount rates. That said, it is not difficult to argue based on his findings that higher inflation might increase the volatility of earnings more than the volatility of discount rates. This might then explain our finding on the relative importances of cash flow and discount rate news in determining the conditional variance of market returns.

4.2 A Closer Look at the Effect of Inflation

In this section, we analyze different dimensions related to the effect of inflation on the conditional variance of unexpected market return and its components as well as on the relative importances of these components. In each of the following subsections, we perform the same analysis as above. Specifically, we first estimate the specification in Equation (7) where we include different inflation components as exogenous variables in the conditional variance of unexpected returns. We then consider these inflation components as exogenous variables in the conditional variance specifications of cash flow and discount rate news in a multivariate conditional variance specification. This allows us to understand the sources of any potential asymmetries in the effects of inflation components on the conditional variance of unexpected returns. Finally, we estimate the specification in Equation (8) where we consider different inflation components as exogenous variables in the system. This, in turn, allows us to analyze potential asymmetries in the effect of different inflation components on the relative importances of cash flow and discount rate news.

4.2.1 The Effects of Positive and Negative Changes in Inflation

We first distinguish between positive and negative changes in the producer price index to analyze any asymmetries between the effects of an increase and a decrease in inflation. In our sample period between 1948 and 2014, inflation increases in 467 months and decreases in 226 months, while it remains unchanged in 110 months. Panel (a) of Table 8 presents the coefficient estimates on the positive and negative changes in the producer price index in the conditional variance specifications of unexpected returns, cash flow and discount rate news. An increase in inflation significantly increases the conditional variances of both cash flow and discount rate news, which in turn explains its positive significant effect on the conditional variance of unexpected returns. On the other hand, a decrease in inflation significantly increases the conditional variance of cash flow news but decreases, although insignificantly, the conditional variance of discount rate news. These mixed results, in turn, explain the insignificant effect of a decrease in inflation on the conditional variance of unexpected returns. Panel (b) of Table 8 presents the coefficient estimates on positive and negative changes in inflation in the equations for the relative importances of cash flow and discount rate news. An increase in inflation significantly increases the relative importance of cash flow news, while it decreases, although insignificantly, relative importances of both discount rate news and the conditional covariance components. The opposite holds for a decrease in inflation. In other words, a decrease in inflation significantly decreases the relative importance of cash flow news, while it increases, although insignificantly, relative importances of both discount rate news and the conditional covariance components. More importantly, both increases and decreases in inflation have significantly different effects on the relative importances of cash flow and discount rate news. These results suggest that both positive and negative changes in inflation affect mostly cash flow news, in line with our previous findings on the effect of the overall change in inflation.

[Insert Table 8 about here]

4.2.2 The Effects of Expected and Unexpected Changes in Inflation

We now distinguish between expected and unexpected changes in inflation, similar to Schwert (1989) and Engle et al. (2013). Specifically, we estimate the following autoregressive model with 12 lags and monthly dummy variables for the change in the producer price index:

$$\Delta \log(ppi_t) = \delta_0 + \sum_{i=1}^{12} \delta_i \Delta \log(ppi_{t-i}) + \sum_{i=1}^{11} \kappa_i D_{i,t} + \mathrm{v}_t \tag{9}$$

where Δ is the first difference operator and $D_{i,t}$ is a dummy variable that takes the value one if the period t is i^{th} month of the year. The fitted values from this model can then be interpreted as the expected inflation while the estimated residual term, $\hat{\mathrm{v}}_t$, can be interpreted as the unexpected inflation. Panel (a) of Table 9 presents the coefficient estimates on the expected and unexpected inflation in the conditional variance specifications of unexpected returns, cash flow and discount rate news. An increase in the expected inflation significantly increases the conditional variances of both cash flow and discount rate news, which in turn explains its positive significant effect on the conditional variance of unexpected returns. On the other hand, the results are somewhat mixed regarding the effect of unexpected inflation. An increase in unexpected inflation significantly increases the conditional variance of cash flow news while it decreases, although insignificantly, the conditional variance of discount rate news. The overall effect of unexpected inflation on the conditional variance of unexpected returns is negative but only marginally significant at the 10% level, suggesting a decrease in the conditional variance of unexpected returns following an increase in the unexpected inflation. When we consider the effect of expected and unexpected inflation on the relative importances of cash flow and discount rate news presented in Panel (b) of Table 9, it is the unexpected inflation that drives the relative importances. To be more precise, expected inflation does not significantly affect any of the relative importances, while an increase in the unexpected inflation significantly increases the relative importance of cash flow news and significantly decreases that of discount rate news. More importantly, the effects of unexpected inflation on the relative importances of cash flow and discount rate news are also significantly different from each other, in line with our findings for the total change in inflation itself.

[Insert Table 9 about here]

4.2.3 The Effects of Inflation in Expansions and Recessions

Here, we distinguish between expansion and recession periods as defined by the National Bureau of Economic Research (NBER) and analyze any asymmetries in the effect of inflation on the conditional variance decomposition of unexpected returns over the business cycles. To this end, we consider the interaction terms between the change in producer price index and recession and expansion dummy variables as exogenous variables in the conditional variance and relative importance specifications. Panel (a) of Table 10 presents the coefficient estimates on the change in inflation in expansions and recessions in the conditional variance specifications of unexpected returns, cash flow and discount rate news. The overall effect of inflation on the conditional variance of unexpected returns and its components is driven by its effects in recessions. To be more precise, an increase in inflation during a recessionary period significantly increases conditional variances of unexpected returns and both of its components. Although an increase in inflation during an expansionary period also increases the conditional variance of unexpected returns, it does not significantly affect the conditional variances of cash flow and discount rate news at the 5% level. Turning our attention to the relative importances, we find that an increase in inflation significantly increases the relative importance of cash flow news in both expansions and recessions, with a slightly bigger effect in recessions. Although inflation decreases the relative importances of discount rate news and the conditional covariance, these effects are not statistically significant at any conventional level. More importantly, the effects of inflation on the relative importances of cash flow and discount rate news are also significantly different from each other during both expansionary and recessionary periods.

[Insert Table 10 about here]

4.2.4 Long-run Effects of Inflation

So far, we have provided empirical evidence on the immediate effect of inflation on the conditional variance decomposition. We now analyze its long-term effect on the relative importances of cash flow and discount rate news. To this end, we compute the impulse response functions of the relative ratios to a standard deviation shock to the change in the producer price index. We do this by estimating a simple first order VAR with the relative importances of cash flow and discount rate news and the change in the producer price index as state variables. Figure 4 presents the generalized impulse response functions as described by Pesaran and Shin (1998), which are based on an orthogonal set of innovations that do not depend on the ordering of the variables in the VAR system.[6]

[Insert Figure 4 about here]

In line with our previous findings, the relative importance of cash flow news increases following a standard deviation positive shock to the change in the producer price index. The impulse response is statistically different from zero since the first month, suggesting

[6] The generalized impulse responses to a specific variable are derived based on the Cholesky factor computed with that variable at the top of the Cholesky ordering. We also considered standard impulse responses where we considered the change in the producer price index as the first variable in the VAR system, assuming that the innovations to the producer price index contemporaneously affect the relative importances of cash flow and discount rate news but not vice versa. The standard impulse responses of relative importances of cash flow and discount rate news are very similar to their generalized impulse responses presented here.

a significant impact response of relative importance of cash flow news to inflation shocks. It continues to remain significant during the following months to reach its peak after 4 months before leveling off after approximately 40 months. Furthermore, it is statistically different from zero after 100 months, suggesting a relatively permanent effect of inflation on the relative importance of cash flow news. The impulse response function of the relative importance of discount rate news reveals results slightly different from our previous findings. Specifically, it is positive but insignificant after one month. It is negative between two and nine months but remains insignificant. After ten months, it is positive but significantly so only after 29 months. These results suggest that inflation does not have a significant effect on the relative importance of the discount rate news in the short run, but it has a significant positive effect in the long run after about 30 months.

Finally, we also analyze whether changes in inflation cause (in the sense of Granger (1969)) the relative importances of cash flow and discount rate news to change. For each equation in the VAR system, Table 11 presents the Wald statistics for the significance of the coefficient estimates on other lagged endogenous variables. The statistic in the last row is the statistic for the joint significance of all other lagged endogenous variables in that equation. There is strong statistical evidence that changes in inflation Granger cause the relative importance of cash flow news to change since we reject the null at any conventional significance level. Changes in inflation also Granger cause the relative importance of discount rate news to change but only marginally so at the 10% significance level. Not surprisingly, the relative importance of each component Granger causes the relative importance of the other to change. Furthermore, relative importance of discount rate news causes changes in inflation while that of cash flow news does not.

[Insert Table 11 about here]

4.2.5 Robustness Checks

In this section, we analyze the robustness of our results on the effect of changes in inflation on the conditional variance decomposition to making alternative empirical assumptions. We performed all the analysis discussed above under alternative empirical assumptions, which we will discuss below. For the sake of brevity, we summarize our findings without presenting all these results, which are available from the authors upon request.

We start with one of the robustness checks in Section 3. Specifically, we consider cash flow and discount rate news proxies obtained based on the sets of predictor variables discussed in Section 3.1. Our results on the effect of inflation on the conditional variances and covariance of cash flow and discount rate news, as well as on their relative importances discussed above, continue to hold when we use these alternative cash flow and discount rate news proxies.

We then consider including inflation volatility as an additional exogenous variable in our analysis. Among others, Schwert (1989) and Engle et al. (2013) provide empirical evidence that inflation volatility is one of the main determinants of stock market volatility. To this end, we obtain two proxies for inflation volatility by estimating a simple GARCH(1,1) model for either the demeaned (total) log changes or unexpected changes in producer price index, the latter of which is calculated as discussed in Section 4.2.2. We then include lagged or contemporaneous values of estimated conditional volatilities from these models as exogenous variables in the conditional variance specifications and relative importance regressions of cash flow and discount rate news. In line with the presented findings, we find that the conditional volatility of unexpected market returns and its components increase with increasing inflation volatility. However, we only find weak empirical evidence of the inflation volatility affecting the relative importances of the components, with the relative importance of cash flow news decreasing with increasing inflation volatility but only marginally significant.

Finally, we turn our attention to the robustness of our results to using alternative sample periods. As discussed in Section 4, we focus on the sample period between 1948 to 2014 in our main set of results, since the unemployment rate is only available starting 1948. However, if we focus solely on inflation, we can consider January 1929 as the starting point as data on *ppi* is available during this earlier period. Thus, we consider this longer period between January 1929 and December 2014 an alternative sample for our results. Furthermore, we split our sample on July 1963 between early and modern periods in our asset pricing tests, following CV, which we will discuss in Section 5. We use this modern period between July 1963 and December 2014 as another sample for our results. We also exclude the period after December 2006 to remove any effect of the financial crisis on our results. We then use the period between January 1948 and December 2006 as an additional sample. Our results based on these alternative samples are quite similar to those based on our original sample, suggesting the robustness of our results to using different sample periods.

5 Economic Importance in the Time Variation of Cash Flow and Discount Rate Betas

In this section, we analyze the economic importance of our results by allowing for time variation in the decomposition of overall market beta. To this end, we follow closely CV which show that the market beta of an asset $\beta_{i,m}$ can be decomposed into cash flow $\beta_{i,CF}$ and discount rate betas $\beta_{i,DR}$ as follows:

$$\beta_{i,m} = \beta_{i,CF} + \beta_{i,DR} \tag{10}$$

where

$$\begin{aligned} \beta_{i,CF} &\equiv \frac{cov(r_{i,t}, CF_t)}{var(r_{m,t} - E_{t-1} r_{m,t})} \\ \beta_{i,DR} &\equiv \frac{cov(r_{i,t}, -DR_t)}{var(r_{m,t} - E_{t-1} r_{m,t})} \end{aligned} \tag{11}$$

However, differently from CV, we are interested in the conditional versions of these betas.[7] Specifically, we obtain conditional betas by estimating multivariate conditional variance models, similar to that in Equations (5) and (6), for the demeaned return on a test asset in addition to the cash flow and discount rate news. However, differently from the models considered in Section 3, we estimate asymmetric, instead of symmetric GARCH models in the first step, which allows us to capture any asymmetries in the conditional variances of returns on test assets.[8] Furthermore, following CV, we also allow for one additional lag of the news components due to the possibility of thin and nonsynchronous trading, especially in the earlier part of the sample, and obtain the conditional cash flow and discount rate betas as follows:

$$\begin{aligned}
\widehat{\beta}_{i,CF,t} &= \frac{\widehat{cov}_t\left(r_{i,t+1},\widehat{CF}_{t+1}\right)}{\widehat{var}_t\left(\widehat{CF}_{t+1}-\widehat{DR}_{t+1}\right)} + \frac{\widehat{cov_{t-1}}\left(r_{i,t+1},\widehat{CF}_{t}\right)}{\widehat{var}_t\left(\widehat{CF}_{t+1}-\widehat{DR}_{t+1}\right)} \\
\widehat{\beta}_{i,DR,t} &= \frac{\widehat{cov}_t\left(r_{i,t+1},-\widehat{DR}_{t+1}\right)}{\widehat{var}_t\left(\widehat{CF}_{t+1}-\widehat{DR}_{t+1}\right)} + \frac{\widehat{cov_{t-1}}\left(r_{i,t+1},-\widehat{DR}_{t}\right)}{\widehat{var}_t\left(\widehat{CF}_{t+1}-\widehat{DR}_{t+1}\right)}
\end{aligned} \tag{12}$$

We consider the standard 25 size and book-to-market sorted Fama–French portfolios as our test assets and obtain their conditional cash flow and discount rate betas as in Equation (12) using monthly data between 1929 and 2014.[9] Figure 5 presents the conditional cash flow

---

7

CV are mostly interested in the unconditional version of their model with betas estimated once over the whole sample period. In their robustness checks, they nevertheless consider conditional covariances estimated using a rolling window of observations. Our results, which we will discuss below, suggest that conditional betas based on multivariate conditional variance models perform better in accounting for the cross-sectional variation in expected returns compared to conditional betas based on rolling window regressions. Our results also suggest that both sets of conditional betas perform better than unconditional betas, which in turn signifies the importance of capturing the time variation in cash flow and discount rate news.

8

$\sigma^2_{i,t} = \alpha_{0,i} + \alpha_{1,i} i^2_{t-1} + \alpha_{2,i} I_{t-1} i^2_{t-1} + \alpha_{3,i}\sigma^2_{i,t-1}$, where i represents the demeaned portfolio returns, CF or DR news. I_{t-1} is equal to one for positive i.

9

CV consider a larger set of test assets which includes the risk-sorted portfolios in addition to the 25 size and book-to-market sorted portfolios. Using their data available on the website of the American Economic Review, we replicated the results reported in their paper. We then considered the smaller set of test assets of 25 size and book-to-market sorted portfolios and found that the results are qualitatively very similar. Thus, we decided to focus on the 25 size and book-to-market sorted portfolios. This choice of test assets also allows us to compare our results with those in literature, which also mainly focuses on these assets. Furthermore, and discount rate betas along with their averages over the whole sample period for the four extreme portfolios: small-growth, small-value, large-growth and large-value portfolios. On average, the cash flow and discount rate betas of small-growth and small-value portfolios are higher than those of large-growth and large-value stocks, respectively. Following CV, we also distinguish between two subsamples: the early period between January 1929 and June 1963 and the modern period between July 1963 and December 2014.[10] In unreported analysis, we computed the averages of the conditional betas in the early and modern samples separately. In the early sample period, both cash flow and discount rate betas are, on average, higher for small and value stocks compared to large and growth stocks. In the modern sample period, small stocks continue to have, on average, both higher cash flow and discount rate betas than large stocks and value stocks also continue to have higher cash flow betas than growth stocks, while their discount rate betas are much lower than those of growth stocks. This pattern in the averages of conditional betas is broadly consistent with those reported in CV.

What is more important for the purposes of our paper is the time variation of conditional betas around their averages. Specifically, in line with our findings for the conditional variances of cash flow and discount rate news, Figure 5 reveals that the conditional cash flow and discount rate betas also exhibit significant variation over time. For example, discount rate betas are slightly higher than cash flow betas in the early sample period for both small-growth and large-growth portfolios but the spread between the two betas for both of these portfolios steadily increases in the modern sample period, reaching its peak around the burst of the dotcom bubble and the ensuing recession. On the other hand, the cash flow and discount rate betas are quite similar over the whole sample period for both small-value and

we also considered including ten portfolios formed on momentum and 30 industry portfolios to the set of test assets. The conditional betas based on multivariate conditional variance models continue to outperform unconditional betas in accounting for the cross-sectional variation in expected returns on portfolios in these larger sets of test assets.

[10] They argue that this sample split makes sense since COMPUSTAT data becomes more reliable beginning July 1963 and the book-to-market anomaly is obtained in the modern sample.

large-value portfolios. That said, the cash flow betas are slightly higher than the discount rate betas in the earlier sample for both portfolios while the opposite holds in the modern period. Figure 5 also reveals that both betas of small portfolios tend to be more volatile than the corresponding betas of large portfolios.

[Insert Figure 5 about here]

Before considering the asset pricing implications of this time variation, we analyze the relation between these conditional betas and inflation, the main macroeconomic determinant of the conditional variance decomposition of market returns. Similar to our analysis in Section 4, we estimate linear regressions of cash flow and discount rate betas on lagged (log) changes in the producer price index. We estimate these linear regressions via SUR while controlling for the lagged values of the corresponding cash flow and discount rate betas in each regression. Table 12 presents the coefficient estimates on lagged (log) changes in the producer price index from these regressions for cash flow betas in Panel (a) and discount rate betas in Panel (b) and their difference in Panel (c). The inflation has a positive effect on the cash flow betas of all 25 portfolios and significantly so for most of them. This effect seems to be stronger on the cash flow betas of large and value portfolios compared to those of small and growth portfolios. On the other hand, the effect of inflation on discount rate betas is mostly negative, but significantly so only for few large portfolios. Unlike the effect of inflation on the cash flow betas, there does not seem to be a clear pattern in the magnitude of the effect of inflation on the discount rate betas of different portfolios. Furthermore, the effects of inflation on the cash flow and discount rate betas of the same portfolio are significantly different from each other, as suggested by significant differences in Panel (c). Overall, these results suggest that the inflation rate is an important determinant of cash flow betas, but not of discount rate betas, in line with our findings in Section 4 where we identify the inflation rate as an important determinant of the conditional variance decomposition of market returns. More importantly, these results show that an increase in the inflation rate significantly increases the cash flow betas, especially those of large and value portfolios. In other words, cash flow risk in equity markets increases significantly following an increase in the inflation rate.

[Insert Table 12 about here]

We now turn our attention to the asset pricing implications of this time variation in conditional betas. Based on Campbell's (1991) approximate discrete-time version of Merton's (1973) ICAPM, CV derive the following asset pricing equation relating the risk premium to cash flow and discount rate betas:

$$E_t\left[r_{i,t+1}\right] - r_{f,t+1} + \frac{\sigma_{i,t}^2}{2} = \gamma\sigma_{p,t}^2\beta_{i,CF_p,t} + \sigma_{p,t}^2\beta_{i,DR_p,t} \tag{13}$$

where $r_{i,t+1}$ and $\sigma_{i,t}^2$ are, respectively, the log return on portfolio i in period $t+1$ and its conditional variance based on information in period t, $r_{f,t+1}$ is the risk-free rate. Equation (13) implies that the risk price of cash flow news should be γ times greater than the risk price of discount rate news, which, itself, should be equal to the variance of the return on portfolio p. CV modify Equation (13) in three ways. First, they use simple, instead of log, returns on the left-hand side of the equation. They argue that using simple returns makes the results easier to compare with those in the literature. Second, they use a market index as the reference portfolio. They argue that this reflects the fact that they are testing the optimality of the market portfolio for a long-horizon investor. Third, they derive an unconditional version of Equation (13) to avoid estimation of the conditional moments. We follow CV and implement the first two of their modifications but ignore the third one since we are exactly interested in the conditional, rather than unconditional, version of Equation (13) and its performance in explaining the cross-section of expected returns.

CV also distinguish between constrained and unconstrained versions of their model. The constrained version, which they refer to as the two-beta ICAPM, imposes the restriction that the risk price of discount-rate news is equal to the variance of the market portfolio. This in turn implies that the only free parameter in Equation (13) is the coefficient of relative risk aversion. The unconstrained version, on the other hand, leaves the risk prices of both cash flow and discount rate betas as free parameters to be estimated. They argue that the unconstrained version can be interpreted as a slight generalization of their model that allows investors' portfolio to include risk-free asset as well as stocks.

In addition to the constrained and unconstrained versions of CV framework with unconditional and conditional cash flow and discount rate betas, we also consider unconditional versions of CAPM and three-factor Fama–French models with constant factor loadings as benchmarks for comparison purposes. We estimate all these models based on the Fama–MacBeth (1973) approach. To this end, we first estimate the following cross-sectional regression in each period:

$$R^x_{i,t} = R_{i,t} - R_{f,t} = \alpha_{i,t} + \sum_{k=1}^{N} \gamma_{k,t}\hat{\beta}_{i,k,t} + v_{i,t} \tag{14}$$

where $\hat{\beta}_{k,t}$ is the beta of the k^{th} factor in an N factor model, and R^x is the simple return in excess of the risk-free rate R_f.

We estimate each model in two different forms following CV. In the first one, we restrict zero-beta rate to be equal to the risk-free rate by estimating the cross-sectional regression in Equation (14) without a constant. This forces each model to explain the risk premia on test assets in addition to the unconditional equity premium. In the second one, we do not impose this restriction and estimate the cross-sectional regressions with a constant. Unlike the first form, the second one does not attempt to account for the unconditional equity premium.

The estimates of risk premia (and the constant) and their standard errors are then obtained as the sample averages and standard deviations (divided by the square root of the number of periods) of the period-by-period estimates, respectively.[11] The performance of each model is evaluated based on three related metrics. The first one is the composite pricing error considered by CV, which is computed as $\bar{\hat{v}}\hat{\Omega}^{-1}\bar{\hat{v}}$ where $\hat{\Omega}$ is a diagonal matrix composed of return volatilities, and $\bar{\hat{v}}$ is the average pricing error. The second one is the number of mispriced portfolios at the 5% significance level based on the t-statistics from the standard Fama–MacBeth approach. The last one is the adjusted R^2 that can be obtained as $1 - \left[{}^{(T-1)}\!/\!{}_{(T-P)}\right] \left[{}^{\left(\bar{\hat{v}}'\bar{\hat{v}}\right)}\!/\!{}_{\left(\left(\bar{R^x} - \mathbf{1}'\bar{R^x}\right)'\left(\bar{R^x} - \mathbf{1}'\bar{R^x}\right)\right)}\right]$ where T is the total number of periods, P is the number of factors including the intercept, and $\mathbf{1}$ is a vector of ones with appropriate dimensions.

When estimating the unconditional models, we use constant betas estimated once using the sample period under consideration. In this paper, we are interested in the performance of the conditional CV framework using conditional betas based on multivariate conditional variance models as described above. For completeness, we nevertheless consider an alternative set of conditional betas based on the covariances and variances estimated from three-year rolling windows of observations, as in CV.

Table 13 presents our results for the modern sample. Before comparing different models, we start by discussing the estimation results for the conditional CV framework with betas estimated based on a multivariate conditional variance model, our main model of interest. First of all, asset pricing theory implies that the constant in the cross-sectional regression should not be statistically distinguishable from zero. The constant in both the constrained and unconstrained estimation of our main model is not significantly different from zero, suggesting that our main model can capture this implication of asset pricing theory. Second, the

[11] CV consider standard errors based on a bootstrap approach instead of the Fama–MacBeth approach. Although their bootstrap approach is relatively straightforward to implement for unconditional models, the same cannot be said for conditional models with time-varying betas. Furthermore, in our replication of CV, we did not find any significant differences between results based on bootstrapped and Fama–MacBeth standard errors, which are identical to those obtained based on a single cross-sectional regression of average returns on unconditional betas for unconditional models. To be more precise, the same coefficients are statistically significant at 5%, which also allows us to compare our results to other studies in the literature.

cash flow news has a reasonable risk price of 1.69% and 1.62% per month in the unconstrained and constrained estimation, respectively. Restricting the zero-beta rate to be the risk-free rate does not alter the results and cash flow beta continues to have a significant risk price. On the other hand, the risk price of discount rate beta is insignificant and small compared to that of cash flow beta. Third, this framework implies very reasonable values of relative risk aversion coefficient (RRA). Depending on whether we impose the zero-beta restriction, the implied RRA is either 3.04 or 4.23 in the unconstrained estimation and either 8.32 or 10.60 in the constrained estimation. Fourth, there are five and seven mispriced portfolios in the unconstrained estimation while there are only three mispriced portfolios in its constrained estimation. This is much better than any other model considered. Furthermore, when we impose the zero-beta restriction in its constrained estimation, it can also account for the expected return on the small-growth portfolio, which is known to be quite difficult to price, while all other models fail to do so. Finally, this model accounts for slightly more than 60% of the variation in the cross-section of expected returns and it is quite stable across different estimations. Overall, these results suggest that our main model of interest provides not only reasonable estimates of risk prices and RRA but also performs quite well in accounting for the cross-sectional variation in expected returns on the 25 size and book-to-market sorted portfolios.

[Insert Table 13 about here]

When we turn our attention to the unconditional models, the economic importance of capturing the time variation in cash flow and discount rate betas becomes clear. We briefly discuss the benchmark models, the CAPM and Fama–French (FF) three-factor model, before turning our attention to the unconditional CV framework. The constant is significantly different from zero for both the CAPM and FF three-factor model when we do not impose the zero-beta restriction. This suggests that both of these models fail to capture the implication of asset pricing theory that the constant should be zero. As it is well known, CAPM performs relatively poorly in accounting for the expected returns on these test assets. It has a very low, or even negative, adjusted R^2 and cannot correctly price thirteen portfolios. On the other hand, FF cannot account for the expected returns on seven to nine portfolios. That said, FF performs quite well in accounting for the cross-sectional variation in expected returns, in terms of adjusted R^2 and composite pricing error. Nevertheless, our main model performs on par with the FF model in terms of adjusted R^2 and better in terms of the number of mispriced portfolios, especially when we impose the restriction that zero beta is equal to the risk-free rate. When we consider the unconditional CV framework, the constant is not significantly different from zero and the cash flow beta has a significantly positive risk price, similar to our main model of interest. However, the unconditional framework implies not only negative RRA values in its unconstrained estimation but also underperforms in accounting for the cross-sectional variation in expected returns relative to our main model of interest.[12] Furthermore, this model results in nine mispriced portfolios compared to three in our main model of interest. These results suggest that ignoring the time variation in cash flow and discount rate news and their relation to stock returns can have important effects on the implications and performance of the CV framework.

Last, but not least, we consider the conditional CV framework where betas are obtained from regressions based on a rolling window of observations. First of all, this conditional

[12] The performance of the unconditional CV framework in its unconstrained estimation is comparable to that reported in CV. On the other hand, its performance in its constrained estimation is quite poor when compared to that reported in CV. In an unreported analysis, we identify two main reasons for this discrepancy. The first, and most important, is the sample period. CV consider the sample period between July 1963 and December 2001, which does not include the financial crisis. We, on the other hand, consider the sample period between July 1963 and December 2014, which does not only include the financial crisis, but also its aftermath. When we estimate the unconditional CV framework for the sample period in CV, its performance in the constrained estimation improves but remains lower than that reported in CV. The second reason is the set of predictor variables used in the VAR to obtain the cash flow and discount rate news. As discussed above, CV use the term spread, small value spread, and price–earning ratio, while we replace the price–earning ratio with the dividend yield. This also affects the performance of the unconditional CV framework but less so compared to the sample period. Nevertheless, the combined effect of the sample period and the set of predictor variables results in the observed discrepancy between the results reported in Table 13 and those in CV. Furthermore, this discrepancy is much lower in the early sample period.

CV model, even if it is based on these betas from rolling window regressions, continues to outperform the unconditional CV model. This in turn points to the importance of capturing the time variation in cash flow and discount rate betas. When we compare the two conditional CV models, the results suggest that the time variation in conditional cash flow and discount rate betas can be better captured by multivariate conditional models than rolling window regressions, and this has important effects on the implications and performance of the CV asset pricing model. To be more precise, the risk price of cash flow beta in the conditional CV model, with betas obtained from rolling window regressions, becomes significant only when we impose the restriction that zero-beta rate is equal to the risk-free rate. This in turn suggests that investors are compensated for holding cash flow risk only when we impose this restriction in this framework. In our main model, the cash flow risk has a significantly positive risk price under both specifications. Similar to the unconditional CV framework, the unconstrained estimation of the conditional CV framework with rolling betas results in negative values for the RRA coefficient and its constrained estimation underperforms in accounting for the cross-sectional variation in expected returns relative to our main model of interest.

5.1 Robustness Checks

Here, we briefly discuss the robustness of the asset pricing results to making alternative empirical choices. For the sake of brevity, we discuss these results without presenting them.

We start with the robustness of our results to using alternative sample periods. Although CV present results for both early and modern sample periods, they mostly focus on the modern sample period for two main reasons. First of all, they argue that book-to-market anomaly is obtained from the modern period. Second, and more importantly, they show that the cash flow beta is practically a constant fraction of the CAPM beta for different assets and, thus, the two-beta model cannot add much explanatory power during the early period. Following CV, we also focus on the modern sample period in this paper. That said, we considered several alternative sample periods including the early sample period. Our results in the early period are broadly consistent with CV and we also find that the CAPM performs on par with the conditional and unconditional two-beta model in the early sample period. More importantly, the conditional framework continues to outperform the unconditional framework in the early sample period but the difference between them is not as pronounced as in the modern sample period. Furthermore, we also considered the modern sample period until December 2001 (the modern sample period considered in CV) and until December 2006 to exclude the financial crisis from our sample.[13] The results based on these alternative modern sample periods are very similar to those presented in Table 13.

We then consider alternative empirical choices in obtaining the proxies for cash flow and discount rate news. Specifically, as in Section 2, we focus on two factors, namely the set of predictor variables and the value of ρ in Equation (4). We consider the same options for these two factors as in Section 3.1 and obtain alternative cash flow and discount rate news. We then repeat our asset pricing exercise using these alternative proxies. Given the high correlation between different empirical proxies of both news components discussed in Section 3, it is then not surprising to find that our conclusions in the asset pricing tests do not change significantly. To be more precise, the conditional framework with conditional betas based on MVGARCH models continues to provide more reasonable estimates and better performance than other conditional and unconditional models considered.

---

[13] To make sure that we omit any impact of the Global Financial Crisis, we also consider an earlier sample ending in June 2006. The results remain similar for this new sample period.

6 Conclusion

In this paper, we analyze the time variation in the decomposition of the conditional variance of market returns as well as its macroeconomic determinants and asset pricing implications. We do this by estimating a multivariate conditional variance model with dynamic conditional correlations for cash flow and discount rate news obtained based on the standard Campbell and Shiller (1988) decomposition approach. Our paper contributes to the existing literature in three empirical dimensions.

First, we provide empirical evidence that not only the components of the conditional market variance but also their relative importances exhibit significant time variation. For example, both cash flow and discount rate news become, on average, more volatile in recessions compared to expansions. More importantly, the relative contributions of these components to the conditional variance of unexpected market returns also vary significantly over time. To be more precise, the contribution of discount rate news varies between 24% and 65%, while that of cash flow news 15% and 61% but is relatively less volatile.

Our second contribution is on the macroeconomic determinants of this time variation. We identify lagged changes in inflation as the main macroeconomic determinant of this time variation in the short run. An increase in inflation makes cash flow news more important and discount rate news less important in the short run. This short-run effect is mostly driven by increases and unexpected changes in inflation during recessions. We also find that an increase in inflation increases the relative importances of both components in the long run at the expense of the relative importance of their conditional covariance.

Our third and final contribution is related to the economic importance of the time variation in conditional cash flow and discount rate betas. We do this by considering its asset pricing implications. Specifically, we argue that it is economically important to account for time variation in beta decomposition if a model which captures this time variation performs better than models ignoring it. To analyze this, we consider a conditional version of the two-beta framework of Campbell and Vuolteenaho (2004) with time-varying betas obtained by estimating multivariate conditional variance models for cash flow news, discount rate news and demeaned returns on the 25 size and book-to-market portfolios one at a time. We show that this conditional asset pricing model provides reasonable estimates and outperforms other conditional and unconditional models in accounting for the cross-sectional variation in expected returns.

From a practical viewpoint, our results might have important portfolio implications for risk-averse investors. For example, our results suggest that both cash flow and discount rate risk vary significantly over time, especially with changing inflation rates. More importantly, we find that the cash-flow risk increases significantly following an increase in inflation. As a result, risk-averse investors might want to tilt their portfolios away from high cash-flow-risk stocks, such as value stocks, or hedge the cash-flow risk of their portfolios more aggressively after observing increasing inflation.

There are several research avenues that we did not explore in this paper. For example, Campbell et al. (2010) decompose the unexpected returns on portfolios, instead of the market, into their cash flow and discount rate news. Similarly, Vuolteenaho (2002) analyzes the unconditional variance decomposition of individual stocks. One can then analyze the conditional, rather than unconditional, variance of unexpected returns on portfolios and individual stocks based on the approach in our paper. We believe that such an analysis might yield interesting insights into the time variation in the relative importances of the two news components in determining the conditional variances of different portfolios and stocks.

References

[1] Bernanke, B. S., Kuttner, K. N., 2005. What explains the stock market's reaction to Federal Reserve policy? Journal of Finance 60, 1221–1257.

[2] Bianchi, F., 2015. Rare events, financial crises, and the cross-section of asset returns. Working Paper, Cornell University, Duke University, CEPR, and NBER.

[3] Callen, J. L., Hope, O., Segal, D., 2005. Domestic and foreign earnings, stock return variability, and the impact of investor sophistication. Journal of Accounting Research 43, 377–412.

[4] Callen, J. L., Livnat, J., Segal, D., 2006. The information content of SEC filings and information environment: A variance decomposition analysis. Accounting Review 81, 1017–1043.

[5] Callen, J. L., Segal, D., 2004. Do accruals drive firm-level stock returns? A variance decomposition analysis. Journal of Accounting Research 42, 527–560.

[6] Campbell, J.Y., 1991. A variance decomposition for stock returns. Economic Journal 101, 157–179.

[7] Campbell, J.Y., Ammer, J., 1993. What moves the stock and bond markets? A variance decomposition for long-term asset returns. Journal of Finance 48, 3–37.

[8] Campbell, J.Y., Mei, J., 1993. Where do betas come from? Asset price dynamics and the sources of systematic risk. Review of Financial Studies 6, 567–592.

[9] Campbell, J.Y., Giglio, S., Polk, C., 2013. Hard times. Review of Asset Pricing Studies 3, 95–132.

[10] Campbell, J.Y., Giglio, S., Polk, C., Turley R., 2017. An intertemporal CAPM with stochastic volatility. Journal of Financial Economics. Forthcoming.

[11] Campbell, J.Y., Polk, C., Vuolteenaho, T., 2010. Growth or glamour? Fundamentals and systematic risk in stock returns. Review of Financial Studies 23, 305–344.

[12] Campbell, J.Y., Shiller, R.J., 1988a. The dividend-price ratio and expectations of future dividends and discount factors. Review of Financial Studies 1, 195–228.

[13] Campbell, J.Y., Shiller, R.J., 1988b. Stock prices, earnings, and expected dividends. Journal of Finance 43, 661–676.

[14] Campbell, J.Y., Vuolteenaho, T., 2004. Bad beta, good beta. American Economic Review 94, 1249–1275.

[15] Cenesizoglu, T., 2014. Return decomposition over the business cycle. Working Paper, HEC Montreal.

[16] Chen, L., Da, Z., Zhao, X., 2013. What drives stock price movements? Review of Financial Studies 26, 841–876.

[17] Chen, L., Zhao, X., 2009. Return decomposition. Review of Financial Studies 22, 5213–5249.

[18] David, A., Veronesi, P., 2013. What ties return volatilities to price valuations and fundamentals? Journal of Political Economy 121, 682–746.

[19] Engle, R. F., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics 20, 339–350.

[20] Engle, R. F., Ghysels, E., Sohn, B., 2013. Stock market volatility and macroeconomic fundamentals. The Review of Economics and Statistics 95, 776–797.

[21] Engsted, T., Pedersen, T. Q., Tanggaard, C., 2012. Pitfalls in VAR based return decompositions: a clarification. Journal of Banking and Finance 36, 1255–1265.

[22] Fama, E. F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

[23] Fama, E. F., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

[24] Feldstein, M., 1980. Inflation and the stock market. American Economic Review 70, 839–847.

[25] Flannery, M. J., Protopapadakis, A. A., 2002. Macroeconomics factors do influence aggregate stock returns. The Review of Financial Studies 15, 751–782.

[26] Friedman, M., 1977. Nobel lecture: inflation and unemployment. Journal of Political Economy 85, 451–472.

[27] Goyal, A., Welch, I., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

[28] Granger, C. W. J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.

[29] Hecht, P., Vuolteenaho, T., 2006. Explaining returns with cash-flow proxies. Review of Financial Studies 19, 159–194.

[30] Holland, A. S., 1995. Inflation and uncertainty: tests for temporal ordering. Journal of Money, Credit and Banking 27, 827–837.

[31] Koubouros, M., Malliaropulos, D., Panopoulou E., 2010. Long-run cash-flow and discount-rate risks in the cross-section of U.S. Returns. European Journal of Finance 16, 227–244.

[32] Lustig, H., Verdelhan, A., 2012. Business cycle variation in the risk-return trade-off. Journal of Monetary Economics 59, S35–S49.

[33] Merton, R. C., 1973. An intertemporal Capital Asset Pricing model. Econometrica 41, 867–887.

[34] Officer, R. R., 1973. The variability of the market factor of the New York Stock Exchange. Journal of Business 46, 434–453.

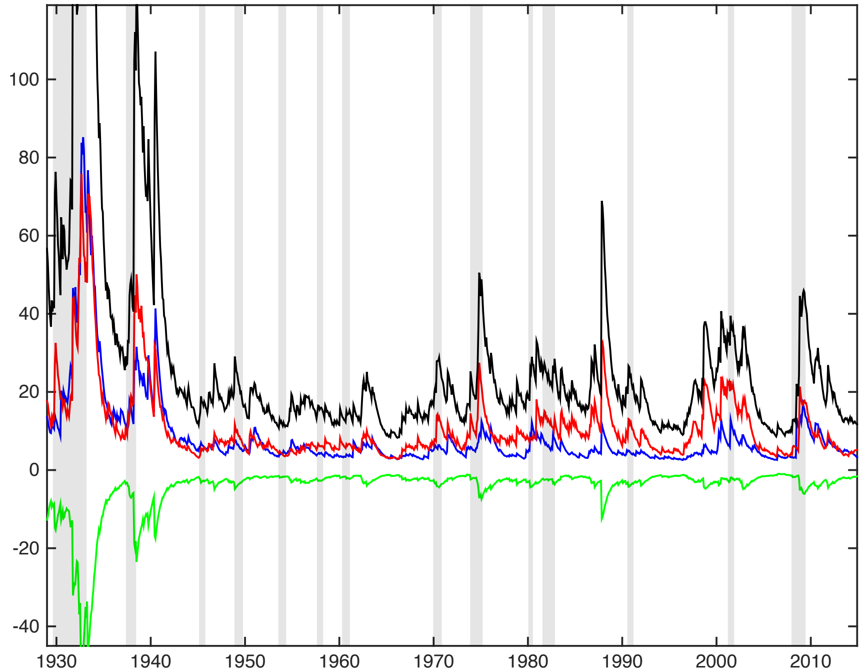
[35] Pesaran, H. H., Shin Y., 1998. Generalized impulse response analysis in linear multivariate models. Economics Letters 58, 17–29.

[36] Schwert, G. W., 1989a. Why does stock market volatility change over time? Journal of Finance 44, 1115–1153.

[37] Schwert, G. W., 1989b. Business cycles, financial crises and stock volatility. Carnegie-Rochester Conference Series on Public Policy 31, 83–126.

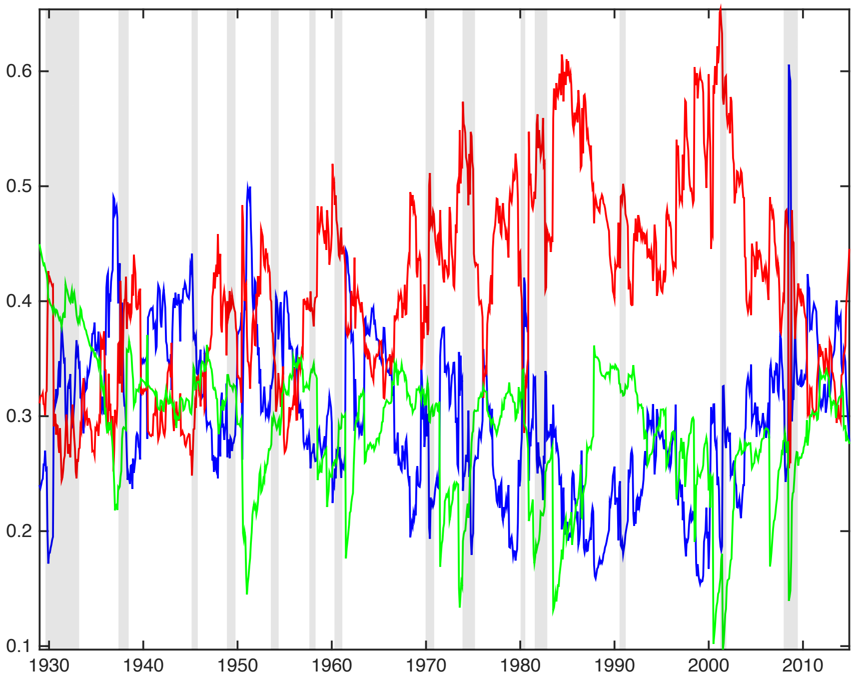
[38] Vuolteenaho, T., 2002. What drives firm-level stock returns? Journal of Finance 57, 233–264.

Figure 1: Conditional Variance of Unexpected Market Return and its Components



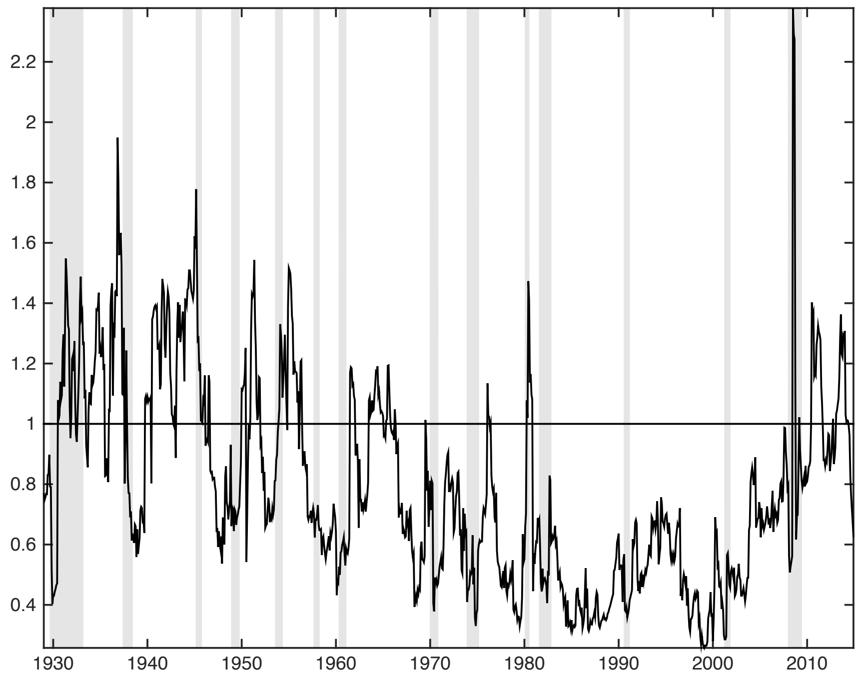
Notes: This figure presents the conditional variance of unexpected returns on the S&P 500 index (black), conditional variance of the cash flow news (blue), conditional variance of discount rate news (red), and the conditional covariance between cash flow and discount rate news (green). The conditional variances and covariances are obtained by estimating the multivariate conditional variance model in Equation (5) and Equation (6) using monthly data between 1929 and 2014.

Figure 2: Relative Contributions of News Components to the Conditional Variance of Market Returns



Notes: This figure presents the ratio of the conditional variances of cash flow news (blue), discount rate news (red) and their conditional covariance (green) to the overall conditional variance of unexpected market returns between 1929 and 2014.

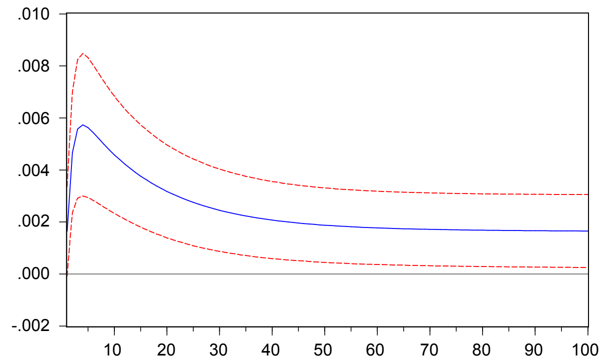
Figure 3: Ratio of the Conditional Variances of Cash Flow and Discount Rate News



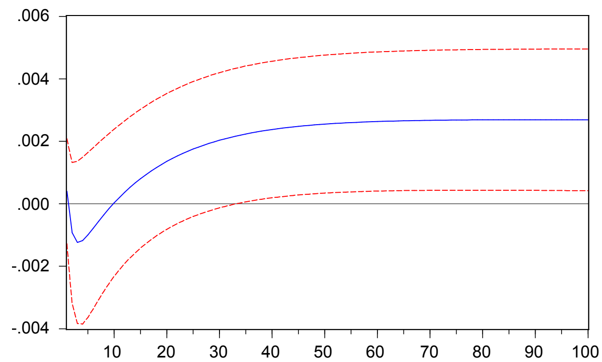
Notes: This figure presents the contribution of cash flow news relative to that of discount rate news between 1929 and 2014. A ratio greater than one implies that the conditional variance of cash flow news is relatively more important than that of discount rate news in determining the conditional variance of market returns.

Figure 4: Impulse Response Functions of Relative Importances of Cash Flow and Discount Rate News to an Inflation Shock

(a) $\sigma^2_{CF,t}/\sigma^2_{m,t}$

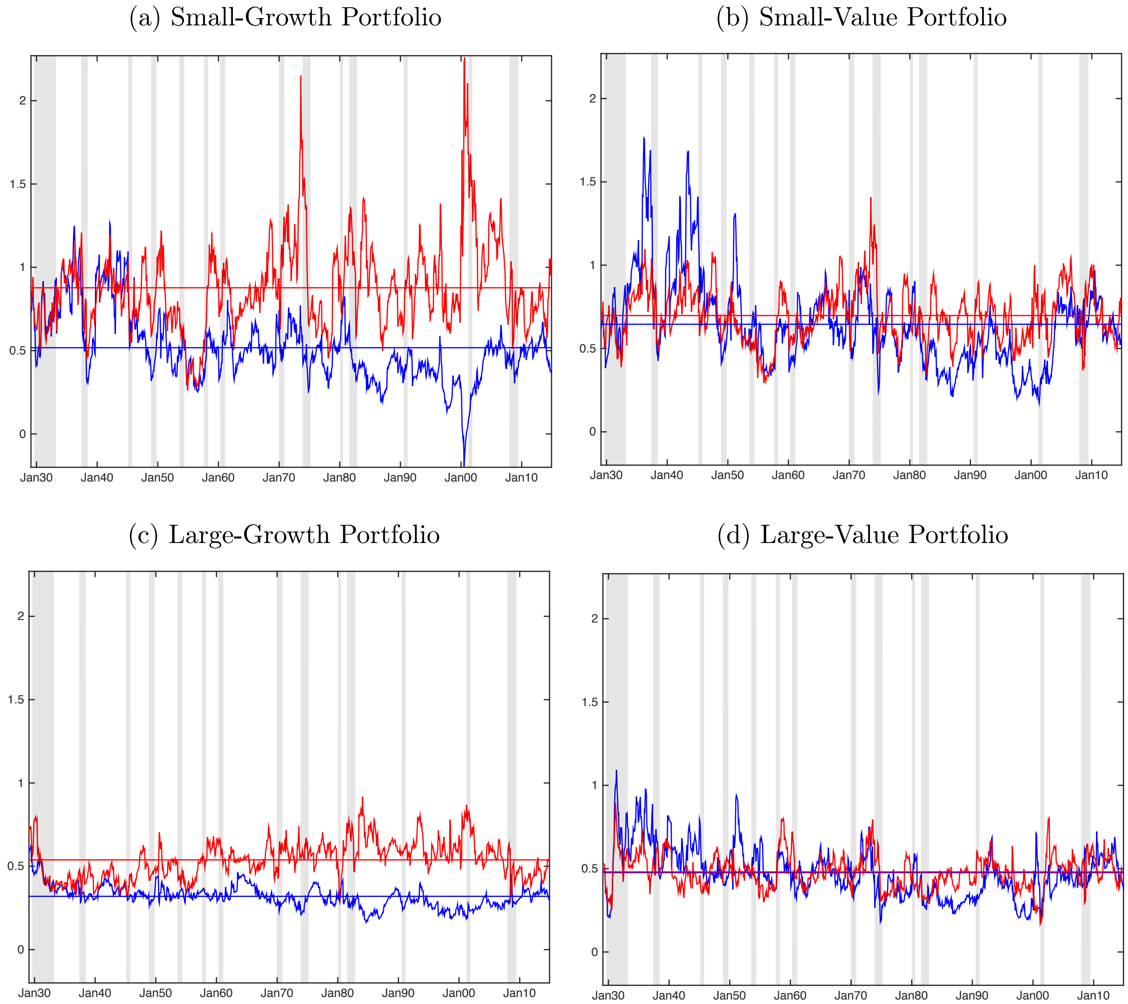


(b) $\sigma^2_{DR,t}/\sigma^2_{m,t}$



Notes: This figure presents the generalized impulse response functions of the relative importances of cash flow (Panel (a)) and discount rate news (Panel (b)) to a one standard deviation positive shock to the change in the producer price index. These generalized impulse response functions are based on an orthogonal set of innovations that do not depend on the ordering of the variables in the VAR system as described by Pesaran and Shin (1998). The dashed lines are the corresponding 95% confidence intervals.

Figure 5: Time Series of the Conditional Cash Flow and Discount Rate Betas



Notes: This figure presents the conditional betas of the four extreme portfolios of the 25 size and book-to-market sorted portfolios between 1929 and 2014. The conditional cash flow (blue) and discount rate (red) betas are obtained based on Equation (12) where the conditional variances and covariances are from the estimation of multivariate conditional variance models for cash flow news, discount rate news and demeaned returns on the 25 size and book-to-market portfolios one at a time.

Table 1: Descriptive Statistics of VAR State Variables

	r_m	tms	dp	svs
Mean	0.0045	0.0175	-3.3604	1.6141
Median	0.0093	0.0178	-3.3373	1.5203
St.Dev	0.0551	0.0130	0.4624	0.3271
Max	0.3463	0.0455	-1.8732	2.6981
Min	-0.3393	-0.0365	-4.5240	1.1861
Autocorrelation (1)	0.0900	0.9595	0.9926	0.9884
Correlations				
r_m	1	0.0508	-0.0788	-0.0383
tms	0.0508	1	-0.1190	0.2147
dp	-0.0788	-0.1190	1	0.2518
svs	-0.0383	0.2147	0.2518	1

Notes: This table presents some summary statistics on the monthly variables in the VAR system. The sample period is between 1929 and 2014. r_m denotes the (log) excess return on the S&P 500 index. tms denotes the term spread computed by subtracting the yield on the three-month Treasury bill from the long-term yield on government bonds. dp is the (log) ratio of 12-month moving sum of dividends to the index level. svs is the small-value spread computed as the difference between log book-to-market ratio of small growth stocks and log book-to-market ratio of small value stocks.

Table 2: Parameter Estimates of the Vector Autoregressive Model

	Const.	$r_{m,t}$	tms_t	dp_t	svs_t	R^2 (%)
$r_{m,t+1}$	0.0405	0.0900	0.2850	0.0081	-0.0087	1.18
	(0.0175)	(0.0311)	(0.1366)	(0.0039)	(0.0056)	
tms_{t+1}	0.0001	0.0018	0.9550	0.0000	0.0004	92.04
	(0.0012)	(0.0021)	(0.0091)	(0.0003)	(0.0004)	
dp_{t+1}	-0.0378	-0.0847	-0.3255	0.9903	0.0066	98.54
	(0.0178)	(0.0317)	(0.1394)	(0.0040)	(0.0057)	
svs_{t+1}	0.0221	-0.0238	0.1464	0.0008	0.9864	97.69
	(0.0158)	(0.0282)	(0.1239)	(0.0035)	(0.0051)	

Notes: This table presents the estimates of the parameters in each equation of the first-order VAR system. The dependent variables are as shown in the first column. Each equation is estimated via OLS and the standard errors are provided in parentheses below. r_m denotes the (log) excess return on the S&P 500 index. tms denotes the term spread computed by subtracting the yield on the three-month Treasury bill from the long-term yield on government bonds. dp is the (log) ratio of 12-month moving sum of dividends to the index level. svs is the small-value spread computed as the difference between log book-to-market ratio of small growth stocks and log book-to-market ratio of small value stocks. R^2 is the adjusted R^2 of the regression. The sample period is between January 1929 and December 2014.

Table 3: Unconditional Variance Decomposition of Market Returns

	Value (basis points)	Relative Ratio
σ^2_{CF}	9.0450	0.3022
σ^2_{DR}	10.8864	0.3637
$-2\sigma_{CF,DR}$	10.0025	0.3342
σ^2_m	29.9340	1

Notes: This table presents the decomposition of the unconditional variance of market returns. σ^2_{CF} and σ^2_{DR} are the variances of cash flow and discount rate news, respectively. $\sigma_{CF,DR}$ denotes the unconditional covariance between cash flow and discount rate news, and σ^2_m is the unconditional variance of unexpected market returns. The Relative Ratio in the last column indicates the contribution of each component to the overall unconditional variance. The sample period is between January 1929 and December 2014.

Table 4: Parameter Estimates of Multivariate Conditional Variance Model for Cash Flow and Discount Rate News

	Coeff.	se	t-stat	p-val
$\alpha_{0,CF}$	0.0000	0.0000	2.3254	0.0202
$\alpha_{1,CF}$	0.0799	0.0198	4.0438	< 0.01
$\alpha_{2,CF}$	0.8930	0.0226	39.5246	< 0.01
$\alpha_{0,DR}$	0.0000	0.0000	2.2088	0.0274
$\alpha_{1,DR}$	0.0982	0.0213	4.6038	< 0.01
$\alpha_{2,DR}$	0.8829	0.0213	41.4450	< 0.01
$(1-a-b)$	-0.4229	0.0573	-7.3817	< 0.01
a	0.0228	0.0158	1.4426	0.1494
b	0.9378	0.0279	33.6369	< 0.01

Notes: This table presents the parameter estimates of the following multivariate conditional variance specification:

$$\sigma^2_{CF,t} = \alpha_{0,CF} + \alpha_{1,CF} CF^2_{t-1} + \alpha_{2,CF}\sigma^2_{CF,t-1}$$
$$\sigma^2_{DR,t} = \alpha_{0,DR} + \alpha_{1,DR} DR^2_{t-1} + \alpha_{2,DR}\sigma^2_{DR,t-1}$$
$$q_{CF,DR,t} = (1-a-b)\,\kappa_{CF,DR} + a\left(\varepsilon_{CF,t-1}\varepsilon_{DR,t-1}\right) + b q_{CF,DR,t-1}$$

where $\kappa_{CF,DR}$ is the unconditional correlation between $\varepsilon_{CF,t}$ and $\varepsilon_{DR,t}$ and $\varepsilon_{CF,t} = {}^{CF_t}/_{\sigma_{CF,t}}$, $\varepsilon_{DR,t} = {}^{DR_t}/_{\sigma_{DR,t}}$. The sample period is between January 1929 and December 2014. Standard errors, t-statistics and p-values are reported in the last three columns, respectively.

Table 5: Descriptive Statistics of the Relative Contributions of Each Component

	$\sigma^2_{CF,t}/\sigma^2_{DR,t}$	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$
Mean	0.7855	0.2983	0.4131	0.2886
Median	0.7032	0.2937	0.4092	0.2978
St.Dev	0.3339	0.0699	0.0878	0.0583
Max	2.3781	0.6059	0.6538	0.4487
Min	0.2573	0.1541	0.2442	0.0970
Autocorrelation (1)	0.9302	0.9293	0.9600	0.9647

Notes: This table presents some summary statistics for the relative contributions of each component to the conditional variance of market returns. $\sigma^2_{CF,t}/\sigma^2_{DR,t}$ is the ratio of conditional variances of cash flow and discount rate news. $\sigma^2_{CF,t}/\sigma^2_{m,t}$ denotes the relative importance of cash flow news variance in the overall conditional variance of unexpected returns. $\sigma^2_{DR,t}/\sigma^2_{m,t}$ is the relative importance ratio for discount rate news and $-2\sigma(CF,DR)_t/\sigma^2_{m,t}$ for the covariance between cash flow and discount rate news. The sample period is between January 1929 and December 2014.

Table 6: The Effects of Macroeconomic Variables on the Conditional Variance of Market Return and its Components

(a) Separate Regressions with Individual Macroeconomic Variables

	r	CF	DR	$F-stat$
ip	0.3166	-62.1794***	-39.5290	0.45
ppi	64.1109***	62.0529***	69.0415***	0.16
$unemp$	-1.5281	13.3032***	4.9769	1.67
emp	60.9110	-158.9785***	21.0644	2.47

(b) Joint Regression with All Macroeconomic Variables

	r	CF	DR	$F-stat$
ip	-15.3363	25.8687	-15.7236	1.10
ppi	65.1310***	61.4467***	66.0295***	0.07
$unemp$	11.3791	10.3585***	8.0658	0.13
emp	136.1793	-136.8803***	86.8085	2.17

Notes: This table presents the effects of macroeconomic variables on the conditional variance of unexpected market return and its components. Panel (a) considers each macroeconomic variable separately as an exogenous variable in the corresponding conditional variance specification. Panel (b) considers all macroeconomic variables jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. ip, ppi, $unemp$, and emp denote lagged (log) changes in industrial production index, producer price index, unemployment rate, and total nonfarm payroll, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 7: The Effects of Macroeconomic Variables on the Relative Contribution of Components to the Conditional Variance of Market Returns

(a) Separate Regressions with Individual Macroeconomic Variables

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
ip	0.1074	0.0199	-0.1274	0.0875
ppi	0.3774***	-0.1818*	-0.1956*	0.5592***
unemp	-0.0185	-0.0003	0.0187	-0.0183
emp	0.1067	-0.0608	-0.0459	0.1675

(b) Joint Regression with All Macroeconomic Variables

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
ip	0.1749	0.0490	-0.2239*	0.1259
ppi	0.3904***	-0.1811*	-0.2093**	0.5715***
unemp	-0.0127	-0.0013	0.0140	-0.0115
emp	-0.5640	-0.0927	0.6567	-0.4713

Notes: This table presents the effects of macroeconomic variables on the relative contribution of each component to the conditional variance of market returns. Panel (a) considers each macroeconomic variable separately as an independent variable in the system in Equation (8). Panel (b) considers all macroeconomic variables jointly as independent variables in the system in Equation (8). The equations in the system are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply the negative of the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. *ip*, *ppi*, *unemp*, and *emp* denote lagged (log) changes in industrial production index, producer price index, unemployment rate, and total nonfarm payroll, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 8: The Effects of Positive and Negative Changes in Inflation

(a) Conditional Variance Specifications

	r	CF	DR	$F-stat$
pos	63.9241***	63.3769***	59.6043***	0.04
neg	74.0019	-47.9991***	442.9469	0.96

(b) Relative Importance Ratios

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
pos	0.3260**	-0.1355	-0.1905	0.4615*
neg	0.4583**	-0.2547	-0.2036	0.7131**

Notes: This table presents the effects of positive (pos) and negative (neg) changes in inflation on the conditional variance of market returns and its components in Panel (a) as well as on the relative contribution of each component in Panel (b). Panel (a) considers positive and negative changes in inflation jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. Panel (b) considers positive and negative changes in inflation jointly as independent variables in the system in Equation (8). The equations in the system in Panel (b) are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply the negative of the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 9: The Effects of Expected and Unexpected Changes in Inflation

(a) Conditional Variance Specifications

	r	CF	DR	$F-stat$
exp	118.0056***	110.1873***	167.0928***	1.04
$unexp$	-33.8324*	40.8453**	-21.6814	2.46

(b) Relative Importance Ratios

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
exp	0.1866	0.0847	-0.2713	0.1020
$unexp$	0.4308***	-0.2565**	-0.1744	0.6873***

Notes: This table presents the effects of expected (exp) and unexpected ($unexp$) changes in inflation on the conditional variance of market returns and its components in Panel (a) as well as on the relative contribution of each component in Panel (b). Panel (a) considers expected and unexpected changes in inflation jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. Panel (b) considers expected and unexpected changes in inflation jointly as independent variables in the system in Equation (8). The equations in the system in Panel (b) are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply one minus the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 10: The Effects of Inflation in Recessions and Expansions

(a) Conditional Variance Specifications

	r	CF	DR	$F-stat$
rec	95.7164***	89.6928***	92.7028***	0.02
exp	37.3141**	28.2022	50.9843*	0.52

(b) Relative Importance Ratios

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
rec	0.4223***	-0.2156	-0.2068	0.6379**
exp	0.3499***	-0.1611	-0.1888	0.5110**

Notes: This table presents the effects of changes in inflation on the conditional variance of market returns and its components in recessions (rec) and expansions (exp) in Panel (a) as well as on the relative contribution of each component in Panel (b). Panel (a) considers changes in inflation in recessions and expansions jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. Panel (b) considers changes in inflation in recessions and expansions jointly as independent variables in the system in Equation (8). The equations in the system in Panel (b) are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply one minus the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 11: Granger Causality Tests

	ppi	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$
ppi does not Granger cause	-	14.5337***	3.1050*
$\sigma^2_{CF,t}/\sigma^2_{m,t}$ does not Granger cause	0.6260	-	19.5218***
$\sigma^2_{DR,t}/\sigma^2_{m,t}$ does not Granger cause	6.9420***	15.3000***	-
All others do not Granger cause	30.3035***	32.8239***	22.5112***

Notes: This table presents the Wald statistics testing the null hypotheses in the first column with the corresponding variables in the headings for the second, third and fourth columns. For example, the first row presents the Wald statistics testing the null that change in inflation does not Granger cause the relative contributions of cash flow (in the third column) and discount rate news (in the fourth column). The last row presents the Wald statistic testing the null hypotheses that the two other variables do not Granger cause the variable in the column heading. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 12: The Effects of Inflation on the Conditional Cash Flow and Discount Rate Betas

(a) Inflation Effect on Cash Flow Betas

	Growth	*Quintile2*	*Quintile3*	*Quintile4*	*Value*
Small	0.0928	0.2178	0.3468**	0.4245**	0.4007*
Quintile2	0.1629	0.3450**	0.3435**	0.3954**	0.2924
Quintile3	0.1312	0.3528***	0.3880***	0.3064*	0.2813*
Quintile4	0.2244**	0.2970**	0.5331***	0.2514	0.4386**
Large	0.3314***	0.4882***	0.5125***	0.4561***	0.3689**

(b) Inflation Effect on Discount Rate Betas

	Growth	*Quintile2*	*Quintile3*	*Quintile4*	*Value*
Small	0.0759	-0.0120	0.0279	0.1333	-0.0072
Quintile2	-0.4059	-0.1696	-0.1545	-0.2466	-0.1809
Quintile3	-0.6103*	-0.2890	-0.0700	-0.2568	-0.1856
Quintile4	-0.5521*	-0.4188**	-0.2917	-0.4394***	-0.3930**
Large	-0.2534	-0.3787**	-0.2272	-0.4451***	-0.3344*

(c) Differences between Effects on Cash Flow and Discount Rate Betas

	Growth	*Quintile2*	*Quintile3*	*Quintile4*	*Value*
Small	0.0169	0.2298	0.3188	0.2912	0.4079*
Quintile2	0.5688	0.5146**	0.4980**	0.6420***	0.4733**
Quintile3	0.7415**	0.6418***	0.4580**	0.5631***	0.4670**
Quintile4	0.7765**	0.7158***	0.8248***	0.6907***	0.8316***
Large	0.5848***	0.8669***	0.7397***	0.9012***	0.7033***

Notes: This table presents the effects of inflation on the portfolio-specific conditional cash flow and discount rate betas in an equation similar to Equation (8), where relative contributions of cash flow and discount rate variances are replaced with the conditional cash flow and discount rate betas, respectively. Panel (a) and Panel (b) consider lagged (log) change in producer price index as an independent variable. The dependent variables consist of cash flow beta (Panel (a)) and discount rate beta (Panel (b)). The equations in the system are estimated via SUR. Panel (c) presents the difference between the corresponding coefficient estimates from Panel (a) and Panel (b) and the significance is based on a Wald statistic testing their equality. *Growth* represents the lowest book-to-market ratio, *Value* the highest book-to-market ratio, *Small* the lowest market value, and *Large* the highest market value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 13: Asset Pricing Results

	Conditional CV Framework with $MVGARCH$ Betas				Conditional CV Framework with Rolling Betas				Unconditional CV Framework with Constant Betas			
	Unconstrained		Constrained		Unconstrained		Constrained		Unconstrained		Constrained	
	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.
α	0.0008	0	0.0008	0	0.0053	0	0.0020	0	-0.0036	0	-0.0065	0
	(0.0023)	0	(0.0026)	0	(0.0021)	0	(0.0022)	0	(0.0039)	0	(0.0035)	0
γ_{CF}	0.0169	0.0163	0.0162	0.0207	0.0100	0.0236	0.0085	0.0162	0.0335	0.0265	0.0266	0.0129
	(0.0051)	(0.0056)	(0.0059)	(0.0060)	(0.0073)	(0.0068)	(0.0056)	(0.0050)	(0.0084)	(0.0057)	(0.0087)	(0.0044)
γ_{DR}	0.0040	0.0054	0.0019	0.0019	-0.0065	-0.0053	0.0019	0.0019	-0.0065	-0.0069	0.0019	0.0019
	(0.0046)	(0.0042)			(0.0048)	(0.0043)			(0.0042)	(0.0040)		
Implied RRA	4.2340	3.0414	8.3173	10.6015	-1.5304	-4.4273	4.5270	8.6192	-5.1699	-3.8276	14.3767	6.9709
Mispriced Portfolios	7	5	3	3	6	8	7	6	13	13	9	9
Adjusted $\widehat{R^2}$(%)	66.49	67.52	66.74	60.86	70.54	49.81	35.87	10.71	52.81	50.58	19.26	11.63
Pricing Error	0.0119	0.0111	0.0113	0.0145	0.0108	0.0169	0.0177	0.0266	0.0166	0.0188	0.0218	0.0260

(a) Conditional and Unconditional CV Models

	$CAPM$		Three-factor FF Model	
	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.
α	0.0113	0	0.0120	0
	(0.0036)	0	(0.0026)	0
$MKT - RF$	-0.0036	0.0066	-0.0066	0.0049
	(0.0040)	(0.0019)	(0.0032)	(0.0018)
SMB			0.0019	0.0020
			(0.0013)	(0.0013)
HML			0.0040	0.0044
			(0.0012)	(0.0012)
Mispriced Portfolios	13	13	7	9
Adjusted $\widehat{R^2}$(%)	6.96	-49.24	71.37	60.08
Pricing Error	0.0377	0.0446	0.0099	0.0130

(b) Unconditional CAPM and Fama–French Models

Notes: This table presents the results from the estimation of the unconditional and conditional CV models in Panel (a) and the unconditional CAPM and FF models in Panel (b). We estimate each model in two different forms. ZB rest. restricts zero-beta rate to be equal to the risk-free rate by estimating the cross-sectional regression in Equation (14) without a constant. ZB. unrest. does not impose this restriction and estimates the cross-sectional regressions with a constant. The estimates of risk premia (and the constant) and their standard errors are obtained as the sample averages and standard deviations (divided by the square root of the number of periods) of the period-by-period estimates, respectively. The cash flow and discount rate news are obtained from the whole sample between January 1929 and December 2014, while the models are estimated over the modern sample between July 1963 and December 2014. The performance of each model is evaluated based on the number of mispriced portfolios, the adjusted R^2s and the composite pricing errors that are presented in the last three rows. In Panel (a), the constraited estimation imposes the restriction that the risk price of discount rate news is equal to the variance of the market portfolio, while the unconstrained estimation leaves the risk prices of both cash flow and discount rate betas as free parameters to be estimated. γ_{CF} and γ_{DR} are the prices of cash-flow and discount-rate risk, respectively. The implied RRA presents the coefficient of relative risk aversion implied by the ratio of γ_{CF} to γ_{DR}. $MKT - RF$ represents the market excess return, SMB the small-minus-big factor, and HML the high-minus-low factor.